DISSERTATION

A SPATIAL DECISION SUPPORT SYSTEM FOR BASIN SCALE ASSESSMENT OF IMPROVED MANAGEMENT OF WATER QUANTITY AND QUALITY IN STREAM-AQUIFER SYSTEMS

Submitted by

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WE HEREBY RECOMMEND THAT THE DISSERTATION PREPARED UNDER OUR SUPERVISION BY ENRIQUE TRIANA ENTITLED "A SPATIAL DECISION SUPPORT SYSTEM FOR BASIN SCALE ASSESSMENT OF IMPROVED MANAGEMENT OF WATER QUANTITY AND QUALITY IN STREAM-AQUIFER SYSTEMS" BE ACCEPTED AS FULFILLING IN PART REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY.

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ABSTRACT OF THE DISSERTATION

A SPATIAL DECISION SUPPORT SYSTEM FOR BASIN SCALE ASSESSMENT OF IMPROVED MANAGEMENT OF WATER QUANTITY AND QUALITY IN STREAM-AQUIFER SYSTEMS

Challenges in river basin management have intensified over the years, with expanding competition among water demands and emerging environmental concerns, increasing the complexity of the decision making framework. State-of-the-art technology is required for assisting water resource managers and decision makers in gaining a better understanding of the river system and in evaluating management alternatives towards optimal utilization of water resources. The sustainability of irrigated agriculture in alluvial valleys is being threatened by increasing pressures from municipalities to acquire agricultural water rights at elevated prices, degradation of agricultural water sources and lands due to salinization, irrigation-induced non-point source contamination of the stream-aquifer system, and non-beneficial consumption of water. A comprehensive spatial-decision support system (*River GeoDSS*) is developed herein to provide assistance in the development and evaluation of management strategies, including structural rehabilitation, for achieving agricultural sustainability, environmental enhancement, and water conservation in irrigated stream-aquifer systems. The *River GeoDSS* provides a comprehensive treatment of water quantity and quality objectives based on conjunctive surface and groundwater modeling within the complex administrative and legal framework of river basin management.

The *River GeoDSS* provides sophisticated tools that allow accurate system simulations and evaluation of strategies while minimizing the technological burden on the user. A unique characteristic of the *River GeoDSS* is the integration of models, tools, user interfaces and modules, all seamlessly incorporated in a geographic information system (GIS) environment that encourages the user to focus on interpreting and understanding system behavior to better design remediation strategies and solutions. The modeling system integrates the comprehensive river basin management model MODSIM with the 3D numerical groundwater quantity/quality model MODFLOW-MT3DMS. The *River GeoDSS* integrates these existing modules with a new artificial neural networks (ANN) module for natural and irrigation return flow quantity and quality evaluation and salt transport through reservoirs, as well as a new water quality module (WQM) for conservative salt transport modeling of conjunctive use of surface water and groundwater resources in the river basin network. The *River GeoDSS* incorporates Geo-MODSIM, a fully functional implementation of MODSIM within the ArcMap interface to the ArcGIS™ geographic information system (ESRI, Inc.). Also incorporated within the *River GeoDSS* is Geo-MODFLOW, a new MODFLOW-MT3DMS results analysis tool in the ArcMap interface. In this research, innovative methodologies are developed for applying ANNs in efficiently coupling surface and groundwater models and carrying out the reservoir salt transport modeling. The WQM's conservative salt transport algorithm, incorporating groundwater contributions within the surface water salinity routing, is fully embedded within the modeling subsystem.

The core *River GeoDSS* is customized to provide comprehensive analysis of alternative solutions to achieving agricultural, environmental, and water savings goals in the Lower Arkansas River Basin in Colorado as a case study for demonstrating the viability of the *River GeoDSS*. The alternatives include basin-scale evaluation of combinations of strategies including (1) aquifer areal recharge (from over irrigation) reduction, (2) canal seepage reduction, (3) improved subsurface drainage under irrigated lands, (4) vertical drainage, and (5) modified reservoir operations, with assurance of physical and administrative compliance. The *River GeoDSS* applied to the Arkansas River Valley allowed comparing benefits and improvements of management strategies, illustrated their potential to reduce waterlogging and soil salinity, salt load to the river, and non-beneficial evapotranspiration in a strategic planning environment.

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PREFACE

The development of *River GeoDSS*, a spatial-decision support system, originated many years of research at field, regional, and basin scales in the Lower Arkansas River Valley (LARV) in Colorado by Colorado State University (CSU) professors Drs. John Labadie, Timothy Gates, and Luis Garcia. The *River GeoDSS* is designed and developed as a flexible adaptable decision support tool to address water resource system-specific issues. The *River GeoDSS* uses MODSIM, a CSU developed and maintained software, as the main modeling engine. The author actively participated in the development of MODSIM version 8 (MODSIM 8), which gives him an invaluable understanding of the model and its state-of-the-art customization capability, essential in the successful implementation of *River GeoDSS*. The initial application of the *River GeoDSS* is in the LARV, Colorado, where earlier investigations identified the need for a basin-wide alternative evaluation tool in moving towards a pilot program implementation of improved water management and salinity control strategies that were developed at field and regional scales. The Lower Arkansas River (LAR) *GeoDSS* is founded upon an unprecedented effort in extensive field monitoring and data collection and many years of field and regional–scale detailed numerical models development by the CSU research team. The *LAR GeoDSS* application presented herein is a promising starting point to developing a tool that can be utilized to answer many emerging questions that will dictate the future of this irrigated river valley.

The *River GeoDSS* final product is a decision support system with core functionality (e.g., the Geo-MODSIM input/output tools, Geo-MODFLOW output display, water quality and artificial neural network modules, and the scenario manager output control) that can be used in any river system with limited case-specific functionality. Customization is necessary to adapt the tool for specific challenges in other basins. The Arkansas River customized version is fully functional for the specific purposes that it was developed for; further improvements and development direction identified during the course of this research are presented.

ACKNOWLEDGMENTS

The author wishes to express sincere appreciation to Prof. John Labadie and Prof. Timothy Gates for their invaluable guidance, assistance, and support during the many years of development of this research project. Their continual encouragement and advice played a key role in the success and completion of this work. The author also would like to recognize the input and comments to the research by his committee members, Prof. Luis Garcia and Prof. Charles Anderson.

Special thanks go to Dr. Phil Burkhalter, for his early work and support on the Arkansas River MODFLOW-MT3DMS regional-scale groundwater model, and to Eric Morway for his assistance in working with, analyzing and understanding the behavior and the assumptions of the regional-scale groundwater model. The author acknowledges Marc Baldo's contribution to the water quality module algorithm design and thanks him for the MODSIM training and support in the early stages of this research. Thanks also are extended to all of the members of the CSU Arkansas River Valley Research Team for their dedication and contributions in building the invaluable framework for this research work.

This research was only possible with the funding and cooperation of many agencies interested in improving conditions in the Arkansas River Valley such as: the Colorado Agricultural Experiment Station, the Colorado Water Resources Research Institute, the Southeastern Colorado Water Conservancy District, the Lower Arkansas Valley Water Conservancy District, the U.S. Bureau of Reclamation and many others. The author appreciates the Colorado Division of Water Resources (Division

2) personnel for their unconditional cooperation, data sharing, and help in understanding the administrative complexity of the Arkansas River system.

Finally, thanks to my wife, my parents, my brother and numerous friends, who endured this long process with me, always offering unconditional support and love.

For my wife Marcela and my sons Mateo and Felipe

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LIST OF ABBREVIATIONS

ANN: Artificial Neural Network

CDWR: Colorado Division of Water Resources

CSU: Colorado State University

DSS: Decision Support System

LARV: Lower Arkansas River Valley

LAR: Lower Arkansas River

NRCS: Natural Resource Conservation Service

SDSS: Spatial Decision Support System

USBR: U.S. Bureau of Reclamation

USGS : United States Geological Survey

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CHAPTER 1

INTRODUCTION, BACKGROUND AND OBJECTIVES

INTRODUCTION

Water systems planning and management include many inseparable elements that make these tasks challenging and complicated. In past years with the abundance and accessibility of computers and software, water systems analysis and decision making have been increasingly accomplished using tools that provide decision makers with valuable information that enhances and facilitates their task. However, when new issues arise, it is often necessary to extend available decision support systems (DSS), if available, or to create new ones to enlarge the knowledge of system behavior, and to aid the decision making process in developing and evaluating management alternatives, including structural rehabilitation, that address the new challenges. Integrated river basin management in which management of water systems is viewed as a part of the broader natural and socio-economic environment is a growing concern for planners, managers and regulators. Effective tools are needed for helping answer questions regarding allocation of scarce resources among competing human activities and for making better decisions on development and sustainable use of water and land resources. Effective river basin management involves not only modeling of the physical river system, but also consideration of the legal-administrative framework and institutional and socio-economic aspects. The work presented herein is an innovative prototype of a spatially distributed river basin scale decision support tool integrating surface and groundwater modeling of water quantity and quality into a river basin management system for effective decision support.

The *River GeoDSS* is developed herein as a spatial-decision support system (SDSS), providing a seamless integration between the spatio-temporal river basin databases and the modeling subsystem. The *River GeoDSS* carries out conjunctive surface and groundwater river basin modeling for water quantity and quality by making use of geo-spatial information and surface and groundwater flow and transport models. The *River GeoDSS* features a water quality module (WQM), allowing integrated modeling of flow quantity and quality, and an artificial neural network (ANN) module for assisting with complex process modeling related to the quantity and quality of natural and irrigation return flows, as well as salt transport through reservoirs. Geographic information systems (GIS) technology is utilized within the *River GeoDSS* to manipulate, process, and store spatio-temporal data. An innovative approach is introduced for accurately modeling the stream-aquifer interactions based on a regional, well-calibrated 3-dimensional groundwater quantity/quality model as an alternative to traditional methods.

Powerful graphical user interfaces (GUIs) and data management tools are incorporated within the *River GeoDSS* to aid users in parameter selection, data entry and processing; ANN training and testing; output display, and management analysis of simulation scenarios. Efficient interfaces are implemented to automate the communication and interaction between models, modules and the underlying spatio-temporal database. The *River GeoDSS* implements MODSIM (Labadie 2006), a state-of-the-art river basin network flow model, as the main modeling engine to carry out the water quantity and quality conjunctive use modeling. MODSIM is selected since it allows not only the water modeling according to physical characteristics and limitations of the system, but also simultaneous modeling of the institutional and administrative elements and regulations. MODSIM is incorporated into the *River GeoDSS* by development of Geo-MODSIM a fully functional version of MODSIM that is incorporated as an extension in the ArcGIS™ geographic information system. The *River GeoDSS* implements a set of customized analysis tools that allow evaluation of "what if" conditions in system operation, irrigation practices, water use, infrastructure improvements, groundwater pumping patterns and water law. The result is a flexible and adaptable tool designed to assist decision makers in comparing and evaluating a wide variety of river basin scale management alternatives.

BACKGROUND

Water quality degradation in agricultural areas can reduce crop yields, thereby threatening the economy and sustainability of rural communities. In addition, water resources are becoming scarcer due to increases in population and the consequential increase in municipal water demands. The expansion of urban populations has generated many municipal water projects focusing on acquiring water rights from agricultural users. Although these projects may be attractive for the depressed economies in the agricultural sector, the outright sale of agricultural water rights to municipalities forecloses future options for the agricultural activity in the river basin. Agricultural water reallocation or changes in agricultural water management practices impact system water users since they change the system dynamics and its equilibrium. Induced changes in irrigation return flow amounts and timing can modify the flow rates and concentration of solutes across the basin, thereby potentially jeopardizing water availability to meet water right entitlements as well as create new environmental and ecological challenges. Therefore, decision making about courses of action requires a broad understanding of the system hydrology, hydraulics, and solute transport, along with environmental, economic, and social aspects. A new focus has arisen on sustainability of agricultural areas that can benefit all users by studying the quantity and quality impacts of changes in water use in these basins. Design of comprehensive solutions for agro-ecological sustainability in irrigated river basins has increased the need to develop powerful support tools that allow addressing complex issues while considering physical, administrative and legal aspects.

The Arkansas River originates in Central Colorado and eventually empties into the Mississippi River. Headwaters of the Arkansas River are located in the 4,267.2-m (14,000-ft) peaks of the Sawatch range of central Colorado, where melting snow is gathered as the primary source of streamflow during October to May. Annual precipitation along the reach of the Arkansas River in Colorado averages less than 254 mm (10 in) east of the mountains, and more than 1016 mm (40 in) per year in the mountain headwaters. The Arkansas River basin in Colorado covers 73,230 km^2 (Figure 1.1). There are several multipurpose systems in the Arkansas River basin. The Fryingpan-Arkansas Project, constructed by the U.S. Bureau of Reclamation (USBR), is a storage and trans-mountain-diversion project that regulates agricultural, municipal and industrial water supplies in Turquoise Reservoir, Twin Lakes Reservoir and Pueblo Reservoir. John Martin Reservoir and the Trinidad Dam and Reservoir Project are primarily flood control projects built by the U.S. Army Corps of Engineers; these projects also regulate irrigation water supplies, and contain recreation pools. The Twin Lakes Project is another storage and trans-mountain-diversion project in the Arkansas Basin, originally developed to serve irrigated lands under the Colorado Canal but, after the sale of the water rights, trans-mountain diversions and storage have become another multipurpose system in the basin. This project, coupled with the Fryingpan Project, provides peak-demand energy generation and additional storage for participants in the Fryingpan Project.

Pueblo Reservoir, located just west of the city of Pueblo, is a multipurpose facility that regulates imported and native water for municipal, agricultural, and industrial use. It contains a joint-use space for flood control in the river from mid April to November. Pueblo Reservoir provides a winter water storage program implemented by the Southeastern Colorado Water Conservancy District and the Colorado Water Resources Division 2, permitting irrigators downstream from Pueblo Reservoir and upstream of John Martin Reservoir to store water in Pueblo Reservoir during the winter months, and to use this water during the crop-growing season. The winter storage program includes off-stream storage and some storage in John Martin Reservoir. Pueblo Reservoir can be used to divide the basin into two sub-basins, each with similar physiographical settings, irrigation practices, and return flow patterns. The Lower Arkansas River Basin in Colorado (Figure 1.1) extends from just below Pueblo Reservoir to the Colorado-Kansas state line, covering about 52,000 km^2 with a main river length of approximately 300 kilometers and containing a total irrigated area of about 1,200 km^2. The Arkansas River is the primary municipal water supply for most of the 170,000 people who live in the five counties that compose the Lower Arkansas River Valley (LARV). The plains agricultural irrigation is based on Arkansas River streamflow diversions to an extensive canal network and on groundwater pumpage.

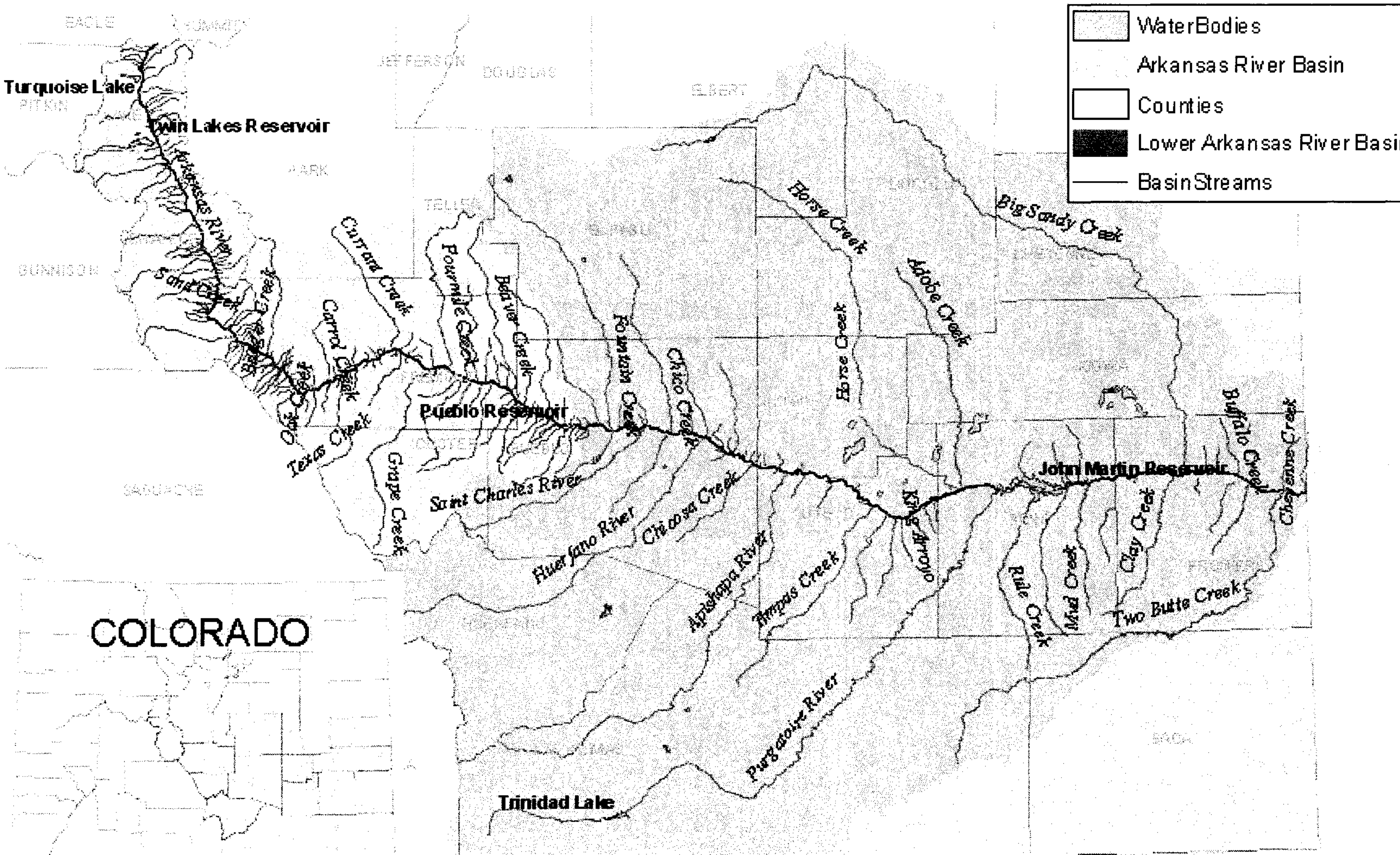

Figure 1.1 – Arkansas River and Lower Arkansas River Basins in Colorado

Waterlogging and salinization is threatening more than 25% of the irrigated land world wide (Tanji 1990; Ghassemi et al. 1995) including the irrigated lands in the LARV. Water in the Arkansas River system is reused several times along the river, where irrigation water infiltrates into the soil, and recharges the alluvial aquifer, with resulting elevated water tables increasing subsurface return flows back to the river. Surface runoff from irrigation enters drains and tributaries that feed the river. These return flows augment natural streamflows for downstream users, especially late in the irrigation season and in fall and winter months. Although users benefit from inefficient water use and return flows, the quality of the water degrades significantly while moving downstream due to dissolution and evaporative concentration. Specifically, salt levels in some stretches of the Lower Arkansas River are approaching one tenth of the concentration found in seawater. Specific conductance, which is directly related to dissolved solids concentration, increases downstream from a median of about 0.5 dS/m (≈340 mg/L) near Pueblo to about 3.9 dS/m (≈3600 mg/L) at Lamar. In fact, the Arkansas River is considered the most saline river of its size in the United States (CDPHE 2002).

High dissolved solids concentrations affect the suitability of water for agricultural, domestic, and industrial uses. Agricultural crop yield losses can occur when dissolved-solids concentrations reach values as low as 700 to 850 mg/L (about 0.95 to 1.2 dS/m). (U S Department of Interior 1994) The secondary maximum contaminant level (SMCL) for dissolved solids in drinking water is 500 mg/L (U S Environmental Protection Agency 1986). The increasing salinity in the Arkansas River in Colorado has been a concern for many years. Konikow and Bredehoeft (1974) developed a flow and salt transport simulation groundwater model for the Arkansas Valley to study the effect of irrigation practices and their relation to the salinity increase. Excess recharge from inefficient irrigation in the basin has caused groundwater levels to rise, creating waterlogging in several areas with the associated problems of salinization (Gates et al. 2002; Burkhalter and Gates 2005; Burkhalter and Gates 2006). Salinization in the soils is demonstrated to be a major factor in reducing crop yields (Gafni and Zohar 2001; Mikati 1997; Patel et al. 2002; Rogers 2002). Based on field data collected between 2002 and 2005, Mueller and Gates (2008) estimated average total dissolved solids (TDS) loadings to the river in an reach upstream of John Martin Reservoir of 8,383 (kg/day)/km and in a reach downstream of John Martin Reservoir of 11,183 (kg/day)/km.

In addition to problems of increased salinity, the Lower Arkansas River is registering selenium (Se) contamination that could threaten the health and safety of humans, animals and aquatic life (Gates et al. 2008). All segments of the Lower Arkansas River are designated as "water quality limited" with respect to Se or/and Fe that have been placed on the current Clean Water Act 303(d) list for TMDL development. Mueller and Gates (2008) investigated and estimated the selenium contamination induced in part by agricultural irrigation practices in a portion of the Arkansas Valley during the period between 2003 and 2005. The average non-point source Se contamination loading to the study area was estimated as 0.038 (kg/day)/km.

Increase in population in cities along the Colorado Front Range has generated a desperate search for new sources of municipal water. The LARV has been targeted by cities such as Colorado Springs, Pueblo, and Aurora as a possible source of water. Many of the proposed options include buying or leasing water from agricultural users, changing points of diversion, and reusing treated waste water from the cities for agriculture. If no actions or provisions are taken promptly, these factors together threaten to permanently harm the already debilitated LARV economy.

High water tables under fallow and naturally-vegetated fields contribute to non-beneficial evapo-transpiration via upflux from the water table through the unsaturated zone. Lower water tables are expected to reduce this water loss from the system (Hallberg et al. 2008).

The LARV in Colorado has been subject to strict regulations in groundwater pumping due to enforcement of court-ordered reparations as a result of lawsuits over violation of the interstate (Kansas-Colorado) river compact caused by post-compact well pumping in Colorado. Kansas claimed that the post-compact well pumping caused additional depletions in the river, diminishing the amounts that were entitled to Kansas in the compact. Therefore, pumping and any other activity that potentially change the pre-compact return flows should be carefully analyzed under the Arkansas River compact.

The Clean Water Act of 1970 and the Federal Water Pollution Act of 1972 were established to unify courses of actions that recognize the important inseparability of water quantity and quality in all water systems. However, many water systems are not managed and regulated to take into account the interaction of water quantity and quality. The State of Colorado is an example of this situation where state policies often divorce the issues of water quality and water quantity. For this reason, agencies such as the Colorado Division of Water Resources, the Colorado Water Quality Control Division, the USGS, the USBR, Water Conservancy Districts, and other decision making entities lack the necessary modeling tools needed to help understand the combined quantity and quality facets of the system. For example, the Supreme Court Kansas v. Colorado case (No 105, 1985) only addresses volumes of water, although the quality of the water could play an important role in the future. This was demonstrated in the case of the Colorado River flow that reaches Mexico (Minute No. 242 of the International Boundary and Water Commission dated August 30, 1973). Integration of water quality and quantity in river basin modeling is not the most common practice. Some models focus on extremely detailed water quantity modeling [e.g., IGSM2 (DWR 2003a, 2003b)], while others concentrate on water quality modeling [e.g., CE-QUAL-W2 (Wells 2000a)]. Dai and Labadie (2001) attempted to integrate water quantity and quality modeling in the Arkansas River basin, but water allocation solutions based on optimizing improvements in water quality (Dai and Labadie 2001; McKinney et al. 1997) would be difficult to implement because of the need to relax the rigorous water laws that dictate water allocation. Water quality needs to be modeled based on viable operational scenarios where water law and river compacts are enforced.

In many cases, analysis of stream-aquifer interaction has been excessively simplified due to the lack of extensive field data. For example, in the Kansas Hydrologic-Institutional Model (HIM) (Burkhalter 1997) applied to the LARV, the groundwater modeling has been performed with sparse field data, thereby limiting the ability of the model to accurately represent basic conditions. Dai and Labadie (2001) used a simplified approach to model groundwater movement and a simplistic method to represent the unsaturated zone. Methods for basin-scale groundwater modeling, especially analytical approaches, rely upon a number of conceptual simplifications, increasing the uncertainty and inaccuracy of the results. Simplifications are often applied to geometry, and to aquifer physical characteristics, for example, such as homogeneity, isotropy, time invariance, and infinite (semi-infinite) aquifer extent. Analytical approaches cannot be applied to groundwater basins with complex boundary conditions and can only approximate the groundwater flow process [e.g., use of Dupuit-Forchheimer assumptions (Dupuit 1863; Forchheimer 1886)]. The primary disadvantage of analytical approaches is that they are not linked to the spatial and physical heterogeneity of the aquifer porous media. In contrast, numerical methods are based on space and time discretization to represent the heterogeneous physical system. However, finite element and finite difference groundwater modeling methods are not efficient when applied over large areas such as an entire river basin. Extensive areas require large numbers of computational elements to accurately represent the system, consuming extensive computer resources. Collecting the necessary data in the field to implement detailed groundwater models such as MODFLOW (McDonald and Harbaugh 1988) and the Integrated Groundwater-Surface water Model 2 (IGMS2) (DWR 2003a, 2003b), and mass transport models like MT3DMS (Xheng et al. 1999), to accurately model a large river basin would be challenging and ambitious. Although, these models can provide more accurate stream-aquifer representation, they lack a powerful surface water module to satisfactorily represent the conjunctive use of water. Sophocleous (1995) compared MODFLOW and the SDF method (Jenkins 1968), which showed considerable discrepancies between the two approaches in representing a real stream-aquifer system. These results were corroborated by Fredericks et al. (1998), who found significant differences using groundwater response coefficients developed from the SDF method compared to using a finite difference groundwater model. There is a need for an alternative methodology that allows accurate basin scale stream-aquifer interaction modeling based on effective field data and detailed groundwater modeling at reasonable computational expense.

Decision making in a river basin system requires assistance from tools that provide an adequate balance between practicality and accurate abstraction of the system. Possibly the greatest challenge when designing a new river basin-scale modeling tool is to understand and overcome the limitations in data collection, availability, and cost. For instance, implementation of a detailed water quality model such as CE-QUAL-W2, a distributed parameter groundwater flow and transport model such as MODFLOW-MT3DMS, or a model within the IGSM2 framework requires extensive and expensive data gathering to accurately calibrate and apply them to a large river basin. Based on current real-world needs, there is an apparent demand for a methodology that provides affordable basin scale tools based on limited but well-conceived field data. The powerful capabilities of geographical information systems, combined with the latest computer programming technology, makes it feasible to conceive an integrated, user-friendly and flexible system achieving a remarkable degree of detail and accuracy in river basin modeling.

The complexity of decision making in river basins encompassing quantity and quality aspects of conjunctive surface water and groundwater use, water law, social groups' interests, and economics requires tools capable of addressing these issues. Although, individual tools help, success derived from combining these tools is becoming increasingly evident. The Yakima River Basin decision support system is a good example of the grouping of tools for enhanced comprehensive studies (McKinney et al. 1997), where the advantages of the concept of SDSS were demonstrated. New developments in SDSSs for evaluating alternatives and quantifying long-term impacts and the potential harm of marked changes in water use, system operations, irrigation practices and infrastructure should effectively blend tools in a geo-referenced graphical user interface and should be spatio-temporal database centered. Emerging technologies such as the .NET framework facilitate the integration of models and the GIS environment, allowing seamless interaction between the internal objects of the DSS components and the construction of new modules for specific modeling tasks. A comprehensive SDSS will facilitate the decision making process and provide better understanding of the system. Initial efforts need to be focused on developing a conjunctive surface and groundwater quantity and quality modeling system that encompasses operational, administrative, and institutional issues designed specifically for river basin scales.

Objectives

Throughout the literature reviewed (Chapter 2), it is possible to identify the scarcity of solutions that bring together both water quality and quantity in a river basin with seamless integration of models in a spatial-temporal data centered fashion. Deficiencies in adequate stream-aquifer representation at the basin scale are revealed. The most common methods are inefficient for large-scale modeling and most of the studies lack the necessary field data for reliable model calibration and testing. These key elements in basin-scale modeling require improvement and special attention to new developments.

The overall goal of this research is to develop a *River GeoDSS* prototype, a generalized basin-scale spatial decision support system for river basin management alternative screening and evaluation. The *River GeoDSS* is conceived as a geo-spatio-temporal database centered system, employing state-of-the-art modeling/computational tools such as

MODSIM, MODFLOW, MT3DMS, artificial neural networks, GIS, and .NET technology to encompass extensive data processing, modeling and DSS customization. By employing digital information, GIS and automated tools for models interaction, *River GeoDSS* can model water resource systems with an unprecedented degree of detail that can be easily managed and utilized for effective decision making.

The *River GeoDSS* development has the subsequent objectives and procedures:

1. Create a set of core tools and interfaces for seamless data and model interaction inside the GIS environment, including data preparation and results presentation, display and analysis.
   1.1. Couple MODSIM, MODFLOW, and MT3DMS with the GIS environment (ArcGIS™), geo-referencing the models' objects and making them available through the GIS interface.
   1.2. Include and combine hydraulic, hydrologic, administrative, operational, and institutional aspects in the modeling system.
2. Develop the *River GeoDSS* spatial-modeling system to carry out dynamic surface and groundwater conjunctive use water quantity and quality modeling for river basins.
   2.1. Create a water quality module to perform conservative solute routing throughout the system and to provide the means to seamlessly interact with surface water and groundwater *River GeoDSS* components.
   2.2. Develop and implement a tool for in-line reservoir water quality transport through the reservoir for comprehensive river basin quality modeling.

2.3. Develop and implement an alternative methodology for efficient basin scale stream-aquifer quantity and quality interaction modeling, and predict the complex stream-aquifer processes for the river basin based on a detailed regional-scale groundwater finite difference flow and mass transport model.

3. Develop and implement tools to expedite and automate the calibration and simulation of the *River GeoDSS* modeling system.
4. Design and implement tools for comparison and analysis of alternative management strategies.

The *River GeoDSS* capabilities are designed to facilitate the decision making process of river basin managers, and are applied and tested in a real-world case study. The Civil and Environmental Engineering Department at Colorado State University (CSU) has been at the vanguard of data collection and modeling in the LARV since 1999 (Gates et al. 2006). Over these years, the CSU research group has compiled a comprehensive set of data and models for understanding the inseparability of water quantity and water quality system behavior. Earlier research in the Arkansas River Valley has allowed the building of an exceptional dataset collected over nine years at both regional and field scales. Salinity and waterlogging effects have been studied in detail. Management alternatives have been engineered and modeled at regional-scale to mitigate these problems and to support agricultural sustainability, environmental enhancement, and water conservation in the area (Burkhalter and Gates 2005; Burkhalter and Gates 2006). Irrigation activities with saline water require a comprehensive analysis beyond the area where water is applied. The basin-scale analysis of field and regional-scale developed solutions will reveal larger-scale benefits and impacts as well as the feasibility of their implementation within a highly-constraint system. This case study is propitious for the *River GeoDSS* application since it can provide the tools necessary for analyzing at the basin scale the management strategies developed at the regional/field scales. Application of *River GeoDSS* to the LARV allows evaluation of large-scale implementation of alternatives to manage present problems and to develop efficient solutions to support a productive irrigated agriculture, to enhance the river environment, and to promote water conservation. The objectives of the *LAR GeoDSS* implementation are:

1. Assemble a robust geo-spatio-temporal database compiling the available digital information from CSU, the USGS, USDA, Natural Resource Conservation Service (NRCS) and others in collaboration with the Colorado Division of Water Resources (CDWR), water conservancy districts, canal companies, and other local agencies.
2. Represent the necessary system elements and the legal, administrative, and institutional rules to accurately reproduce historical weekly system operation while integrating hydrologic processes, water rights, storage accounts, water compacts, water exchanges, and physical system limitations.
3. Apply the *River GeoDSS* methodology to represent the stream-aquifer interaction at the basin scale using the available calibrated regional-scale groundwater model. The conjunctive use of water quantity and quality modeling will facilitate the screening of improvement strategies under appropriative water rights and other legal, institutional, and administrative structures in the basin for implementation decision making.
4. Evaluate river basin response to the regional-scale developed water management alternatives including improvements in irrigation practices, pumping patterns and infrastructure improvements such as canal lining and subsurface drainage installation.

5. Evaluate effects in water quality due to changes in reservoir operations, water use and management alternatives implementation.

CHAPTER 2

LITERATURE REVIEW

RIVER BASIN FLOW MODELING AND DECISION SUPPORT SYSTEMS

MODSIM is a generalized river basin network flow model (Labadie 2006), allowing not only representation of physical system features and processes, but also artificial and conceptual elements permitting flexibility in allocating water according to complex hydrologic, administrative, legal, and institutional/contractual mechanisms. MODSIM allows runs in calibration mode and in management mode, and includes stream-aquifer interaction modeling with user defined or model generated stream-aquifer response coefficients. The MODSIM Graphical User Interface (GUI) allow users to build the system topology, enter data and parameters and display the results in graphical or tabular form. The current interface lacks the ability of interacting with geo-referenced data directly. An outstanding MODSIM capability is that it allows customized code to be compiled with the main program, thereby enhancing flexibility in modeling complex behavior and rules and allowing integration of models and modules. It has been successfully applied in many river basins around the world encompassing institutional, administrative, and economic issues [e.g., the Gunnison River basin (Weiss et al. 1997), upper Snake River basin (Larson et al. 1997), South Platte River basin (Fredericks et al. 1998), Piracicaba River basin in Brazil (De Azevedo et al. 2000) and Friant Division

Project of the Central Valley Project in California (Marques et al. 2003)] . MODSIM is public-domain software that does not require a license purchase.

MODSIM can address environmental and water quality issues when used in conjunction with other models (Dai and Labadie 2001; Campbell et al. 2001; De Azevedo et al. 2000). MODSIMQ extends MODSIM to include surface water quality routing using an iterative connection with EPA QUAL2E (Brown and Barnwell 1987) and a soil column model for predicting salinity loading in irrigation return flows (Dai and Labadie 2001). MODSIMQ is able to model water quantity, water quality, and administrative/institutional aspects. QUAL2E is a 1D stream-water quality routing model (Brown and Barnwell 1987) able to simulate up to 15 water quality constituents, including dissolved oxygen, biochemical oxygen demand, temperature, algae as chlorophyll a, organic nitrogen as N, ammonia as N, nitrite as N, nitrate as N, organic phosphorous as P, dissolved phosphorous as P, coli form, an arbitrary non conservative constituent and three user define conservative constituents. The MODSIMQ groundwater component contains an unsaturated zone water quality model that accounts for chemical reactions, ion exchange and a steady-state saturated zone model with conservative assumptions for the transport of constituents. The groundwater component is a simplified representation of the complexity of basin scale modeling. It shares the MODSIM interface but lacks of a user friendly interface for QUAL2E. MODSIMQ assures convergence to a solution that maintains minimum water quality requirements. Although water allocation according to water rights priorities is included, MODSIMQ solution may adversely affect senior water rights since the primary goal is maintaining water quality standards. Dai and Labadie (2001) applied MODSIMQ to the LARV in Colorado for development of salinity control strategies. In this study, irrigation return flows, canal seepage, reservoir seepage, deep percolation, and river depletion due to pumping were modeled using stream depletion factors developed by the U.S. Geological Survey (Jenkins et al. 1972). The stream-aquifer interaction was modeled over monthly time steps, with major ion relationships used to estimate salt loads in the groundwater return flows similar to the approach presented by Cain et al. 1987.

RiverWare is an interactive object-oriented model to simulate all major river basin features including reservoirs, streamflows, diversions, and lagged returns flows (Zagona et al. 2001). It includes operational rules for reservoir releases and river diversions, and can be run using specified inflows and outflows, rule-based simulation, or optimization techniques. RiverWare uses the concept of a groundwater storage object that provides tools to model aquifer flow; however, the module's effective application requires detailed prior knowledge of system behavior or a detailed model to select the required object parameters. The RiverWare literature reviewed show an elaborate GUI but does not indicate the ability to geo-reference the model objects or use of spatio-temporal databases. This model lacks the ability to customize runs using outside programming code, thereby limiting its ability to be integrated with other models or modules. RiverWare is able to carry out water quality calculations by simulating total dissolved solids, temperature, and dissolved oxygen. For modeling total dissolved solids only, a simple, well-mixed model is also available. Temperature and DO models use a 2-layer reservoir model and discretized reaches in which the water quality equations are coupled with hydraulic routing, either with or without dispersion. RiverWare requires an expensive license and annual maintenance contract.

CALSIM is a generalized water resources simulation model for evaluating operational alternatives of large, complex river basins (Andrew et al. 2004). Originally developed by the State of California Department of Water Resources, CALSIM efficiently allocates water using a linear programming solver. Groundwater has only limited representation in CALSIM; it is modeled as a series of interconnected lumped-parameter basins. Groundwater pumping, recharge from irrigation, stream–aquifer interaction, and inter-basin flow are calculated dynamically by the model. Its GUI allows basic display of the system features, data, and plotting capabilities. CALSIM II, developed by the California Department of Water Resources in conjunction with the USBR, includes a GIS tool to execute the model from a GIS network. CALSIM integrates a simulation language for flexible operational criteria specification, but is unable to handle custom code for additional module integration. These combined capabilities provide a comprehensive and powerful modeling tool for water resource systems simulation. Even though CALSIM does not require a license, it needs commercial software to operate; plans to upgrade to a public-domain solver were found in the literature.

CE-QUAL-W2 is a finite difference water quality and hydrodynamic model in 2D (longitudinal-vertical) model for rivers, estuaries, lakes, reservoirs and river basin systems (Wells 2000a). CE-QUAL-W2 offers detailed water quality constituent modeling, including generic constituents [conservative tracers, water age or hydraulic residence time, coli form bacteria, and contaminants], inorganic suspended solids groups, phytoplankton groups, epiphyton groups, CBOD groups, ammonium, nitrate-nitrite, bioavailable phosphorus, labile dissolved organic matter, refractory dissolved organic matter, labile particulate organic matter, refractory particulate organic matter, total inorganic carbon, alkalinity, total iron, dissolved oxygen, organic sediments and gas entrainment. Accurate use of this model is limited by the discretization required in the finite difference models, thereby making it inefficient and difficult to apply to large basins.

MIKE BASIN is a river basin management tool in GIS developed by DHI Software (www.dhisoftware.com). That addresses water allocation, conjunctive use, reservoir operation, or water quality issues. This tool is designed to use GIS processing and display features coupled with hydrologic modeling for basin scale planning and management. Hydrologic modeling is achieved by representing the system using nodes and links. The new MIKE BASIN 2005 is implemented as an ArcGIS (ESRI®) extension with an integrated time series database. The model uses GIS geometric networks to represent the system topology, and the water allocation algorithm uses local or global rules to allocate water. The rules can define local priorities for riparian doctrines and global priorities for the prior-appropriation doctrine. MIKE BASIN is unable to handle delays in the flows in the global allocation of water such as occurring in groundwater modeling and channel routing. This tool calculates aquifer return flows to the stream using a simplified method based on a linear reservoir model with one or two aquifers (Fast/Slow response). The stream-aquifer interaction modeling requires the user to define time series corresponding to the stream seepage and the aquifer recharge. Realistic groundwater modeling in this tool is limited since the method is not linked with spatial-varied physical aquifer properties and spatial-temporal-varied system stresses such as recharge, sub-surface drainage and seepage. The water quality solution assumes purely advective transport, although decay during transport can be modeled. MIKE BASIN can model quality in the groundwater assuming in the conceptual model a perfect mixing in each aquifer (first order decay can also be modeled). MIKE BASIN allows user control of the simulation using VBA in ArcGIS; the ability to use this customization ability to link to other models or modules is not specified in the documentation. This commercial software requires the purchase of a license and ArcGIS as interface (stand-alone interface is not available).

Burns (1988) developed an interactive accounting model to simulate streamflow, water quality, and water supply operations in the Arkansas River basin. The model used regression equations to compute flow from incremental drainage areas by using a time series of independent variables, such as snow-pack, precipitation, or gauged flow. In this model the dissolved solids were computed from regression equations with streamflow as the independent variable. The model is applicable to a large lumped-area, thereby lacking the ability to analyze localized problems. The model as applied to the Arkansas Valley was calibrated to compute dissolved solids based on observed streamflow throughout the basin. Three sites in the basin were used for calibration in which daily specific conductance was used to determine observed monthly dissolved solids loads. Regression coefficients used for the calculation of dissolved solids were developed by Cain et al. (1987).

WEAP (Water Evaluation and Planning system) is a model developed by the Stockholm Environment Institute for water resources planning (Yates et al. 2005). The newest version features dynamic linkage with MODFLOW and QUAL2E for water quality modeling. WEAP introduces in this version the ability to use an Application Programming Interface to execute and control inputs/output of the model using programming code (including VBA, Visual Basic or scripting languages). WEAP claims to have objects geo-referenced but it is not reported whether the interface has GIS functionality for spatial data processing or display.

Decision support systems (DSS) are interactive programs, often with a graphical user interface (GUI), which embed traditional water resources simulation and optimization models, with adaptation of new approaches, to support users in semi-structural or ill-structural problem solving (Loucks and da Costa 1991). The Colorado River Simulation System (CRSS) model is implemented using the rule-based simulation capabilities in the RiverWare (Schuster 1989). The CRSS was developed in response to a need for a modeling system that could simulate operations for various hydrologic and demand sequences along the Colorado River. CRSS evaluates how proposed development occurring high in the basin might impact locations downstream from the development. The CRSS includes a flow simulation model of the entire Colorado River system. It also includes a stochastic natural flow model to generate future stochastic flows and a salt regression model that estimates natural salinity associated with natural flows.

A widely used DSS in Colorado is the Colorado's decision support system (CDSS), developed by the Colorado Water Conservation Board (CWCB) and State of Colorado Division of Water Resources (DWR) (CWCB and DWR 2002). The CDSS has been implemented in the Colorado River basin (CRDSS) (including divisions 4,5,6, and 7), the Rio Grande basin (RGDSS), and the South Platte basin (SPDSS) currently under development. These DSSs are centered on a database called HydroBase. The CRDSS focuses on surface water modeling and administration, the RGDSS extends the analysis to groundwater and surface water modeling. The CDSS includes (1) a surface water planning model (STATEMOD), (2) a consumptive water use model (STATECU (CWCB and DWR 2007)) that bases its estimates on spatial irrigation acreage data in a GIS and interacts with STATEMOD, (3) a web site for distributing project data and results, and (4) a number of other Colorado River modeling tools. The groundwater modeling efforts vary by basin; the RGDSS groundwater is modeled using MODFLOW, and the input data files are generated using: (1) basin GIS coverages and ArcView avenue pre-processing scripts, (2) the GMS model interface, (4) the STATECU model, and (5) the STATEMOD model. STATECU provides consumptive water use (CU), canal loss, surface water applied, and pumping based on historical data. STATEMOD allocates water under the prior appropriation doctrine based on user defined operating rules, providing the same data that STATECU uses to build the MODFLOW input files. From the literature reviewed, the CDSS lacks the capability for accurate modeling of the interaction between surface water and the groundwater. The groundwater model requires inputs from the surface water model, but it is not clear how the dynamic stream-aquifer interaction is modeled.

Mastin and Vaccaro (2002) developed a decision support system for the Yakima River Basin in eastern Washington. This DSS consists of three major components: a river and reservoir management model (RiverWare), a modular modeling system (MMS) that calculates runoff, and the central hydrologic database (HDB). The USGS MMS is an integrated system of computer software developed to provide a framework for the development and application of numerical models to simulate a variety of water, energy, and biogeochemical processes (Leavesley et al. 1996). The model for runoff prediction in the MMS is the USGS Precipitation-Runoff Modeling System (Leavesley et al. 1983). The HDB contains metadata and historical and real-time hydro-meteorological data. It allows for easy data query and display through graphical-user and data-management interfaces. The HDB acts as the bridge between RiverWare and MMS by accepting model input and output. The Yakima DSS uses a GIS interface, called Weasel (Leavesley et al. 1997), which is used to delineate watersheds and sub-basins, in addition to assisting in the construction of the model. Although the Yakima DSS utilizes detailed, spatially-varied data such as Digital Elevation Models (DEM), land use/land cover, soil layers, and forest-cover type and density, it lacks of detailed spatially-varied precipitation data for hydrologic modeling. The stream-aquifer interaction modeling is limited to determining percentages of total streamflow corresponding to surface runoff, sub-surface runoff and groundwater flow (Risley 1994), with the percentages varying according to the underlying soil of each sub-watershed. The Yakima DSS uses the Object User Interface to integrate the models, display data, initialize simulations, and transfer data to the database in an attempt to provide real-time operations support. No documentation was found for consideration or specific modeling of water quality aspects in this DSS.

Westphal et al. (2003) developed a DSS for short term planning (7 days) based on forecasted climatic conditions. The DSS is developed in Microsoft EXCEL and links a hydrologic model, reservoir hydraulic models, and a reservoir water quality model with linear and nonlinear optimization algorithms. The DSS offers the ability to optimize daily and weekly reservoir operations toward four objectives based on short-term climate forecasts: maximum water quality, ideal flood control levels, optimum reservoir balancing, and maximum hydropower revenues. Since there is no interaction between the DSS and a GIS, the DSS does not consider any spatially-varied information on the modeled basins. The stream-aquifer interaction is carried out using the *abcd* model developed by Thomas

(1981), which uses four physically-based parameters (*a*, *b*, *c*, and *d*) to estimate inputs and outputs from the aquifer and the surface soil moisture. Total organic carbon in one of the reservoirs modeled, but provides only coarse detail on the modeled basin, focusing primarily on the reservoir states. The literature does not indicate the ability of modeling detailed water allocation according to water rights.

McPhee and Yeh (2004) used groundwater simulation and optimization to construct a decision support system (DSS) for solving groundwater management problems in the Upper San Pedro River Basin (Arizona). A previously developed steady and transient finite difference model (MODFLOW) was used to simulate groundwater flow. The DSS provided a framework to aid decision makers in defining the best groundwater pumping and recharge policies in the basin by explicitly considering environmental, economic and development objectives.

Wurbs (2005) presents a package for river/reservoir system management (WRAP). This tool is implemented in Texas for assessing water resources availability and reliability, and is implemented to handle water allocation under water rights and analyze impacts of water management decisions. Work is reported on development of user interfaces and integration with GIS, but the main interface is limited to definition of input file locations, template generation, modules execution and linkage to HEC-DSSVue (USACE 2006), a Java-based GUI program for viewing, plotting, editing, and manipulating data in HEC-DSS (USACE 1995) database files. Wurbs et al. (1995) reports an application of an earlier version of WRAP in conjunction with the RESALT model for salinity considerations in evaluation water supply capabilities of reservoir systems. Wurbs applied WRAP model to the Brazos

River Basin in Texas. RESALT is similar to HEC-HMS (Hydrologic Engineering Center's Reservoir operation simulation software (USACE 2007)) to simulate sequential operation of a reservoir-channel system with a branched network configuration including salinity modeling. Improvement of the salinity modeling is proposed as a future enhancement.

Geographic Information Systems in Water Resources

Srinivasan and Arnold 1994 developed a modeling system that integrates the Soil and Water Assessment Tool (SWAT) (Arnold 1992) with GRASS, a U.S. Army GIS system (USACE 1988). The modeling system uses GIS as a tool to define modeling parameter (e.g., watershed runoff, stream characteristics, slopes, watershed boundaries, and flow direction) and aggregate inputs for its distributed basin scale model (SWAT). This research demonstrated the effectiveness of using GIS to automate model input to assist with management of runoff, erosion, pesticides, and nutrient movement in large basins.

ArcHydro is a water resources data model applied within geographic information system (GIS) technology to provide a variety of hydrologic solutions (Maidment 2002). ArcHydro generates both raster and vector watersheds map layers based on Digital Elevation Models (DEM). A DEM is a grid in which each cell is assigned the average elevation over the area represented by the cell. ArcHydro also builds sub-watersheds for user-defined points within the system, and allows users to build hydro-networks of rivers and streams from the generated watersheds. ArcHydro offers functionality to assign unique identifiers to system features (HydroID), allowing establishment of relationships between features and data in the database. In addition, ArcHydro provides a data structure (i.e., a standardized template) allowing linkage between hydrologic data and water resources models and synthesis of geospatial and temporal water resources data. This template can be used for something as basic as hydrologic data storage, or for something as complex as executing regional interoperability and data sharing between local and state agencies with joint control over water resources. ArcHydro itself does not offer functionality to model water movement or water quality within the system.

Olivera et al. (2003) highlighted the ability of ArcHydro to facilitate interchange of spatial and temporal hydrologic information among applications. They demonstrated the data interchange between ArcHydro and the Hydrologic Model System (HEC-HMS (USACE 2007)), developed by the U.S. Army Corps of Engineers' Hydrologic Engineering Center in Davis, California, as an example of the hydrologic data integration. Maidment (2002) presented successful applications of ArcHydro concepts in the Guadalupe River Basin, Trinity River Basin, and San Marcos River Basin in Texas. These applications demonstrate drainage systems, and hydrography and hydrologic modeling. The Guadalupe River Basin case study illustrated the development of hydro networks and the relationship between hydro-junctions and system features such as monitoring points, water bodies, and drainage areas.

Shannon et al. (2000) developed a tool that provided a metadata framework for linking GIS coverages with the procedural MODSIM river basin network flow model. GIS was applied to synthesizing spatially-distributed steam-aquifer response coefficients for inclusion into MODSIM for conjunctive management of surface water and groundwater resources in a river basin. Application of the principle of superposition (Bear 1979) allows individual excitation events to be calculated independently and the responses linearly combined. In this case, response of the groundwater system due to external excitations such as pumping, recharge or infiltration at any point in space and time can be expressed as a set of unit coefficients independent of the magnitude of the excitation. The linearity assumption can produce errors when the groundwater flow characteristics as not linear such as for unconfined aquifers with drawdown exceeding 10% of the original saturated thickness, the linearity assumed could lack credibility when large amounts of complex simultaneous events are to be represented. However, in this case, the response coefficients can be recalculated based on the new levels in the aquifer. This tool was applied to the Lower Snake River flow augmentation study by Johnson and Cosgrove (1999), where stream-aquifer interaction in the basin was modeled using MODRSP (Maddock and Lacher 1991)-calculated response functions for each cell on the river reaches cells. Although the groundwater model cell size was relatively coarse ($25Km^2$), the compiled results require an extremely large database that is difficult to edit, maintain and process. Preprocessing of the database is necessary for efficiently running MODSIM using the response coefficients. Proposed future work includes a direct linkage between GIS and MODSIM by importing response functions and extracting river basin topology directly from geo-datasets.

McKinney et al. (1997) developed a prototype GIS-based decision support system for river basin management in ArcView GIS (ESRI, Inc.). The prototype is based on an extension of the concept of decision support system called spatial decision support system (SDSS). The SDSS is an integration of GIS and DSS, as first suggested by Densham and Goodchild (1989). In an SDSS, the system is represented using spatial objects and thematic objects, with the spatial objects representing the real world entities and the thematic objects including the network, attributes, logical and political relations; and models. The prototype system automatically generated a physical node-link system representation based on the spatial relationships of the system features. The system features (nodes) are automatically connected using links that are derived from the spatial relation functions. The user manually modifies the automatically generated network (i.e., adds or deletes nodes and links) to build the final network required for the particular study. A user interface integrated into ArcView allows entry of external information to build the system model. Having all the system features and connections in the network explicitly defined results in a cumbersome representation of the system, making the network dense and difficult to manipulate and explain to those unfamiliar with the model since it appears quite different from the real system. The GUI created for this prototype is a good example of a graphical-spatial interface with fully integration of the model inside a GIS package. The purpose of the research was to develop a water allocation tool. Water was allocated by solving an optimization problem that combines six objectives using user defined weights, subject to constraints on physical, policy and system control requirements. The objectives included in the optimizations are: (1) maximize the satisfaction of water demand, (2) minimize the differences in water shortages, (3) maximize downstream flow in the main river, (4) minimize salt concentrations in the water system, (5) maximize satisfaction of hydropower generation demands, and (6) minimize the amount of water diverted from other basins. The model allocates water based only on the optimization of the pre-defined objectives, and lacks the ability to allocate water according to the prior appropriation doctrine. It also appears to be difficult to implement complex river operations such as exchanges, reservoir accounts and reservoir operations.

STREAM-AQUIFER INTERACTION

The increasing stress on water systems has highlighted the inseparable relationship between surface water and groundwater resources since the development of either groundwater or surface water affects the other (Winter et al. 1998). Therefore, adequate representation of stream-aquifer interaction is a major concern for developing accurate basin scale models, especially in basins where return flows and depletions constitute a significant portion of the surface water flow.

Stream-aquifer interaction is a complex phenomenon to understand and model. Streams can gain water from the groundwater or lose water to groundwater, as illustrated in Figure 2.1. The direction of the flow changes seasonally, temporally and spatially as water levels in both the aquifer and the stream change with respect to each other. Stream can be connected to groundwater through the saturated zone, or disconnected with an unsaturated zone in between, with the former resulting in more rapid responses to changes in the system. As shown by Morgan and Jones (1999), pumping from an aquifer also directly affects the stream-aquifer interface due to the propagation of pumping impacts in all directions in unconfined aquifers. This example showed how surface water is captured spatially within the basin after the groundwater system has achieved equilibrium. Hubbell et al. (1997) studied the temporal effects on surface water discharge prior to the groundwater system achieving a equilibrium state. This study highlights the importance of taking transient response times of groundwater systems into account in long-term water resources planning.

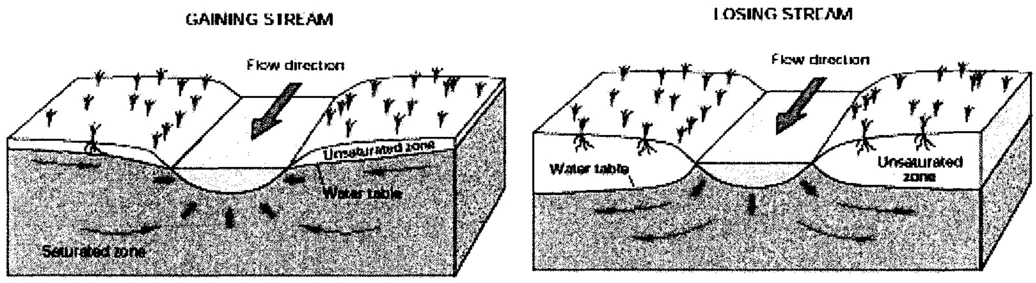

Figure 2.1 – Stream-aquifer interaction [modified from Alley et al. (1999)]

For more than 50 years, researchers have studied stream-aquifer interaction and have developed methodologies to represent it. Analytical solutions approximate groundwater systems with simplified approaches. The parallel drain analogy describes stream-aquifer system interaction as flow between two parallel drains (Maasland 1959).

A popular method based on the Glover (1974) solution is the stream depletion factor (SDF) method (Jenkins 1968), where SDF is a system descriptor with time dimension. The method predicts the volumetric change in streamflow due to recharge or withdrawal of water from the aquifer by merging spatially-varied hydraulic properties, aquifer stress locations, and types of boundaries. Jenkins et al. (1972) calculated SDF values for the LARV, making available hydrologic maps and response coefficient tables to estimate monthly changes in streamflow due to aquifer recharge or withdrawal.

Frevert (1983) estimated subsurface flow to the river using the Dupuit-Forchheimer approximations, such as the segmented model and the segregated model. These methods assume the hydraulic gradient at any point to be equal to the slope of the water table above the point and the equipotential lines to be parallel to each other. The segmented model divides the irrigated area above the alluvial aquifer into three areas parallel to the river segments, and relies on well defined hydrological and agricultural parameters. The segmented model lacks the ability to predict year-to-year changes and peaks in return flows, and is unable to simulate lags between diversions. Since the segregated model calculates evapotranspiration, effective precipitation, and subsurface flow, Frevert (1983) concluded that this method as more flexible in the prediction and timing of peak return flows than the segmented model.

Stream-aquifer interaction has been modeled using approaches that do not rely on hydrological, geological, or agricultural parameters. The Nash Model utilizes a general response function based on a model consisting of a number of equivalent linear reservoirs (Nash 1968). The formulation does not rely on hydro-geologic parameters, but instead needs the estimation of theoretical parameters during the calibration process. The model uses evapotranspiration, effective precipitation, and deep percolation for all irrigation systems in one alluvial valley and uses a convolution process to calculate the return flows. The Nash Model seems to accurately predict year-to-year fluctuations, varying the annual carryover effect through the calibration process. The multiple correlation model is a statistical model that estimates return flow based on a regression approach, optimizing parameters to minimize the error between the predicted and the measured data (Frevert 1983). This model uses hydrological, climatological (e.g., temperature, sunshine factor, and precipitation) and agricultural conditions as input variables. Existing stochastic models for analyzing flow in heterogeneous media (Li and McLaughlin 1991) are either based on assumptions that are too restrictive to be applicable at real-world field sites, or computationally cumbersome and expensive to be practically implemented at sites of realistic sizes.

Hydrologic watershed modeling studies have addressed the issue of modeling stream-aquifer interaction by estimating the return flows from groundwater as a portion of the surface flow in the stream at the watershed outlet. The "abcd" model is a nonlinear watershed model the produces streamflow based on precipitation and potential evapotranspiration as model inputs (Thomas 1981). The model internally accounts for groundwater storage, soil moisture storage, direct runoff, and groundwater outflow to the stream channel. The model parameters *a*, *b*, *c*, and *d* have physical interpretation, where parameter *a* is the propensity of runoff before the soil is completely saturated, parameter *b* is the sum of actual evapotranspiration and soil moisture, *c* is the fraction of streamflow arising from groundwater discharge in a given month, and the reciprocal of the parameter *d* is associated with the average groundwater residence time.

With similar but more elaborated approach, the precipitation-runoff modeling system (PRMS) is a deterministic, physical-process-modeling system designed to analyze the effects of varying climatological and land use conditions on streamflow, sediment yield and general basin hydrology (Leavesley et al. 1983). Risley (1994) calibrated the PRMS model for 11 small drainage basins in Oregon, with each basin conceptualized as an interconnected series of reservoirs whose collective output produces the total hydrologic response. These reservoirs include interception storage in vegetation, impervious-area storage on the surface, storage in the root zone, subsurface storage between the surface of the basin and the water table, and groundwater storage. Model calibration consists of estimating parameter values to minimize the error between the observed and predicted basin-outlet flows. Risley (1994) uses all the studied drainage areas at the same time for calibration to provide regionalized parameters that assist in hydrologic simulation of other gauged and ungauged basins in that region. Defining the parameters controlling the subsurface and groundwater contribution rates is difficult with use of any measured, physical basin data. These parameters are usually estimated using optimization tools (Rosenbrock 1960) and have been found to be the most sensitive of the calibration parameters (Allen and Antonius 1993). Therefore, the prediction of return flows using these methods is not expected to be accurate since there are many other factors that control the physical process that will be included in these calibration parameters as results of the optimization process. In addition, this method lacks the ability to predict spatially varied stream-aquifer interaction within the basin.

CALVIN (CALifornia Value Integrated Network Model) is a network-flow based economic-engineering optimization model developed at the University of California, Davis (Howitt 1999, Jenkins and Calfed Bay-Delta Program 2001). This model uses a simplified representation of the aquifer in order to apply optimization to the conjunctive use of surface and groundwater resources. Groundwater basins are represented as lumped reservoirs with a fixed capacity, and are treated in the same manner as surface reservoirs (Jenkins and Calfed Bay-Delta Program 2001). The groundwater reservoirs dynamically interact with the surface system driving the optimization process.

MODFLOW, the USGS Modular Three-Dimensional Ground-Water Flow Model (McDonald and Harbaugh 1988), is a widely used groundwater finite difference model to simulate groundwater elevations or piezometric surfaces and groundwater flow. The model requires the creation of cells to represent the modeling space and a detailed description of the system hydraulics. Some of the required model data includes hydraulic conductivity, transmissivity, specific yield, boundary conditions (i.e., locations of impermeable and constant head boundaries), and stresses such as pumping wells, recharge from precipitation and irrigation, rivers, and drains. MODFLOW is organized into modules, with each module including packages that control specific aspects of the simulation. The MODFLOW-streamflow routing package is used to simulate stream-aquifer interaction in intermittent streams by calculating stream/canal stages using Manning's equation, known stage values, or a values table to calculate inflow and outflow to the aquifer from the stream by limiting aquifer recharge to the water available in the stream. The package allows merging of stream branches and simulation of diversions.

As discussed previously, stream-aquifer interactions can be represented by "response functions" that describe the relative response of the aquifer system at a given location due to a unit change in the stress (recharge/pumping) at another location. Because the response is expressed in relative terms, it may be scaled to any magnitude of stress desired. The functions may express transient or steady-state response of the system to the stress. The development and use of response functions requires that the response is proportional to the magnitude of the stress; consequently, the governing equations must be approximately linear. Similar or identical concepts have been called discrete kernels (Morel-Seytoux 1975), influence coefficients (Illangasekare and Morel-Seytoux 1982), algebraic technologic functions (Maddock 1972) and drawdown simulations (Anderson and

Woessner 1992). The assumption of linearity of the governing equations is the major drawback in the application of response function methodology.

Numerical models such as MODFLOW or MODRSP (Maddock and Lacher 1991), which is a modified version of MODFLOW, generates response functions by applying MODFLOW to stress all individual grid cells and determine the resulting unit response at the river cells. This method is extremely demanding in terms of data requirements, with most of the inputs variable in space and some variable in time. Some of the inputs include, but are not limited to, stream and reservoirs cells definition with information about water elevation and parameters such as hydraulic conductivity and conductance (as a function of the stream bed materials and physical characteristics); aquifer transmissivity, groundwater system boundaries, and excitation cell locations such as pumping wells, aquifer recharge, reservoir seepage, or channel losses. Response coefficients for river reaches can be generated by combining individual results in all cells in the reach for incorporation of response functions into the surface water models such as MODSIM.

AQUATOOL, a decision support system developed by the DIHMA of the Polytechnic University of Valencia (Andreu et al. 1996), uses an approach similar to MODSIM for simulating systems using optimization techniques. AQUATOOL implements a conjunctive groundwater and surface water modeling in the water system simulation. The aquifer is simulated using several approaches, ranging from simplified reservoir/pumping only to elaborated distributed parameter model. The groundwater module is integrated with the tool network flow solver using an iterative procedure, where the network solution is used in the groundwater module providing information for the next iteration of the network flow solution. Paredes-Arquiola et al. (2004) implemented GESCAL, an interface that couples QUAL2E and the AQUATOOL modules, to simulate several water quality constituents in rivers and reservoirs. GESCAL is applied to observe water quality changes from various operational scenarios and their effect on planning future treatment plant facilities.

The Kansas Hydrologic-Institutional Model (HIM) (Burkhalter 1997), which was specifically developed for purposes of the Supreme Court Kansas v. Colorado case regarding the violation of the Arkansas River compact. The model is applied to estimating flow in the Arkansas River that would have occurred in the absence of post-compact well pumping in Colorado. HIM uses a mass balance approach to simulate water quantity only, and models the Arkansas River from the downstream end of Pueblo Reservoir to the Colorado-Kansas state border over monthly time steps between the years 1950 and 1994. The model takes into account 25 water users and eight reservoirs and accounts for some operational characteristics such as the prior appropriation doctrine, the winter water storage program, and trans-mountain water. The estimated streamflow is then used to determine whether Colorado has met its obligation under Article IV-D of the compact to ensure that any new water development in Colorado has not materially depleted Arkansas River flow at the Colorado-Kansas border. The model has been modified and updated several times over the years by modelers in both Colorado and Kansas. More recently, the courts have stipulated that the HIM model requires more accurate determinations of crop consumptive use as calculated by the Penman Montieth Method using updated and improved data sets, with the resultant consumptive use estimates then input into the HIM Model. The HIM Model is not accurate on either annual basis or short-term basis, as stated by the Special

Master in the Kansas v. Colorado case. The Special Master adopted the Colorado proposal to apply the model over a ten-year period in order to average out errors. It is believed that the primary source of error is the lack of an accurate stream-aquifer modeling component. In contrast, the methodology presented in this research includes detailed regional scale models that provide a strong basis for accurately representing the stream-aquifer interaction.

The Integrated Ground water-Surface water Model (IGSM2), developed by the State of California Water Resources Department Modeling Support Branch of the Bay-Delta Office, simulates groundwater flow, surface water flow, and surface-groundwater interaction (DWR 2003a, 2003b). The model simulates groundwater elevations and horizontal and vertical groundwater flow in a multi-layer aquifer system using the Galerkin finite element method to solve the non-linear conservation equation. IGMS2 uses a similar approach to the MODFLOW streamflow-routing package to model surface water flow and stream-aquifer interaction. Four land use categories are used to dictate the evaporation, surface runoff, and infiltration characteristics as well as agricultural and urban water demands. Direct runoff is updated using a rainfall-runoff relation developed by the National Resources Conservation Service based on a curve number (*CN*) which indicates runoff potential. Diversion water and pumping water is distributed to meet agricultural and urban water requirements. IGSM2 was applied to the California Central Valley Project Improvement Act studies and many regional applications throughout California and the United States. For example, the CALFED Program for developing and implementing a long-term comprehensive plan to restore ecological health and improve water management for beneficial uses in the California Bay-Delta System, has used IGSM2 for integrated storage investigations. The model lacks a powerful water allocation algorithm, and assumes prior knowledge of diversion and bypass water for stream modeling. The amount of return flow from irrigation and urban water use is computed as a pre-specified fraction of the water applied to agricultural and urban lands.

ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANN) are "massively parallel interconnected networks of simple elements and their hierarchical organizations which are intended to interact with the objects of the real world in the same way as biological nervous systems do" (Kirby 1993), or simply a "system of interconnected computational units" (Kirby 1993). A simple neural network (NN) consists of an input layer, a hidden layer and an output layer. These layers have a number of nodes or neurons. Input nodes receive data from sources external to the network and send them to the hidden nodes, in turn the hidden nodes send and receive data only from other nodes in the network, and output nodes receive and produce data generated by the network which goes out of the system (Govindaraju and Rao 2000).

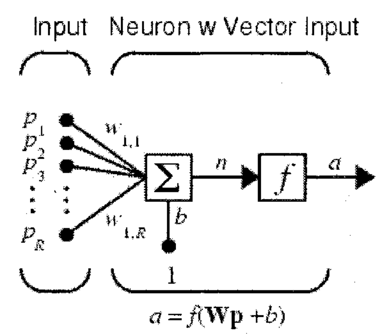

Figure 2.2 – Simple neuron diagram

The NN basic information-processing unit is the *neuron* (as descried on Haykin 1994). The neuron consists of: (1) a set of connecting links, each link characterized with a weight (*w*) or strength, (2) a *combiner* that combines all the signals multiplied by their corresponding weights and (3) an *activation function* for limiting the amplitude of the output. Usually the neuron activation input (*n*) is combined with a *bias* term (*b*). Figure 2.2 shows representation of a simple neuron with bias (Hagan et al. 1996). p_i is the *i* neural net input and R is the number of elements in the input vector. Activation functions transfer the neuron activation inputs (n) to the next layer; the most common are linear (*purelin*), hyperbolic tangent sigmoid transfer function (*tansig*), log-sigmoid (*logsig*), triangular basis and radial basis (*radbas*).

Backpropagation Neural Networks

The NNs in this group are characterized by having a common training procedure. The term *backpropagation* refers to the manner in which the gradient is computed for nonlinear multilayer networks. Standard backpropagation is a gradient descent algorithm, as is the Widrow-Hoff learning rule (Rumelhart et al. 1986), in which the network weights are moved along the negative of the gradient of the performance function.

Feed-Forward NN

This type of network is based on the *perceptron* concept introduced by Rosenblatt (1962), which projects the input nodes onto hidden layers and output nodes exclusively, with no connections in the opposite direction. This ANN receives weighted inputs from nodes in the input layer, and with each succeeding layer receiving weighted inputs only from the preceding layer. Figure 2.3 shows a diagram with an example of a two layer feed-forward NN. The example NN has two input variables (p_i), and four hidden neurons in the first layer (each one with a bias) and three hidden neurons in the second layer. $IW_{1,1}$ = input weights matrix for the first layer with source in the first layer. $LW_{2,1}$ = the layer weights matrix with source in layer 1 and destination layer 2. Bias (b_i), net input (n_i), and output (a_i) have a superscript i to say that they are associated with the network layer i. The transfer functions in Figure 2.3 example are tangent sigmoid for the first layer and linear in the second layer.

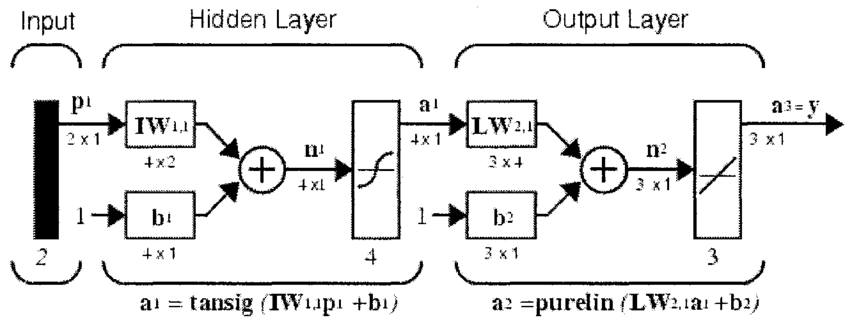

Figure 2.3 – Feed-forward neural network example

Elman NN

This network feeds back to nodes in the input layer the output generated by the input layer nodes (Elman 1990). This recurrent connection allows the Elman network to both detect and generate time-varying patterns. Figure 2.4 shows a diagram of the network structure, where the delay [D] uses first layer outputs from the previous time step (*k-1*). This network stores information for future reference, being able to learn temporal as well as spatial patterns. This network differs from the Jordan neural network (Jordan 1990) in having recurrence on the layer output it self rather than on the network output (a_2). The Jordan NN uses as "internal" input from the previous time step outputs.

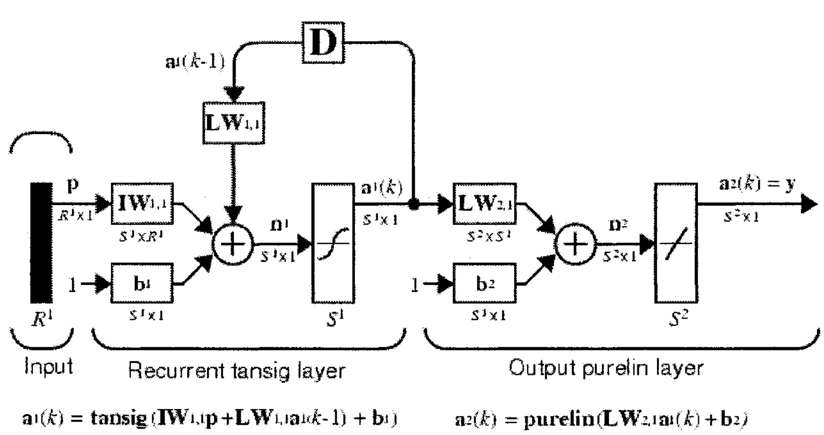

Figure 2.4 – Elman NN structure diagram

Cascade-Correlation-Forward Networks

This network structure and training algorithm is introduced by Fahlman and Lebiere (1990). In this type of feed-forward network, the first layer has weights coming from the input. Each subsequent layer has weights coming from the input and all previous layers. All layers have biases. The last layer is the network output. The training algorithm adds hidden neurons to a multi-layer structure and trains the new unit individually, claiming to speed up the learning process.

Radial Basis Networks

This type of network includes two layers: a radial basis layer and a linear layer (Haykin 1994;Chen et al. 1991). The radial basis layer is characterized by using a radial transfer function *radbas* defined as:

$$radbas(n) = e^{-n^2}$$

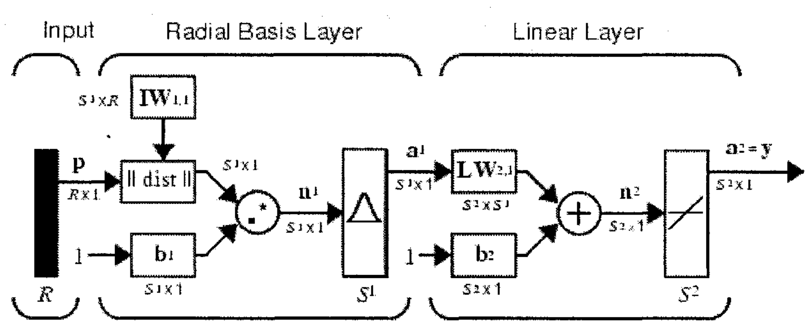

Figure 2.5 – Radial Basis Network structure diagram

In Figure 2.5, R = the number of elements in the input vector, S^i= number of neurons in layer i. $\| Dist \|$ = the distances between the input vector and vectors i in rows of the input weight matrix ($IW_{1,1}$). The bias b_1 elements, in the first layer, are multiplied time the elements of the $\| Dist \|$ vector (element-by-element multiplication). The bias allows the sensitivity of the *radbas* neuron to be adjusted.

Generalized Regression Network

This special type of radial basis neural network, introduced by Specht (1991), has a special linear layer (second layer). The outputs from the first layer (a^1 on Figure 2.5) are combined with the row of the layer weights ($LW_{2,1}$) using a dot product, resulting in a vector with S^2 elements.

Application of ANN in Water Resources

Several successful applications of ANN in water-related problems are found in the literature. Particularly in the groundwater modeling area, Maskey et al. (2000) trained a network to approximate groundwater flow and transport as predicted by the models MODFLOW and MODPATH. The ANN training and validation showed its ability to predict modeled-site clean up time and clean up cost to a reasonable accuracy. Results showed a better performance in predicting smaller clean up times. For a sub-group of predictions consisting of the smallest 50 % of the predictions, the ANN was able to predict the model output with coefficients of determination ranging from 0.95 to 0.97. An advantage reported in this study is that the ANN reduces the computation time in simulation processes compared with traditional (physically-based) models. An ANN model is much faster than the physically-based model that it approximates, facilitating the application of optimization routines to the problem. Once an ANN is suitably trained to imitate a particular aquifer system, it can be applied for further use in optimal management of the system (Das and Datta 2001). Rogers (1992) and Rogers (1994) employed an ANN, which was trained by a solute transport model, to perform successful optimization studies in groundwater remediation. For training of an ANN for a groundwater system, it is necessary to use several groundwater responses corresponding to a variety of aquifer stress scenarios.

Darsono and Labadie (2007) presented a good example of machine learning application to optimal real-time regulation of flows and in-line combined sewer system. This study trains a Jordan neural network (Jordan 1990) on the optimal policies generated by an dynamic optimal control module, demonstrating the advantages of using recurrent type NNs in time-varying patterns process.

The role of ANNs in various branches of hydrology was examined by Govindaraju and Rao (2000). It was found that ANNs are robust tools for modeling many nonlinear hydrologic processes such as rainfall-runoff, stream flow, groundwater management, water quality simulation, and precipitation. After appropriate training, they are able to generate satisfactory results for many prediction problems in hydrology. Jia and Culver (2003) applied the bootstrap technique to train an ANN for synthetic flow generation with a small data sample. The advantages of this technique are the ability to estimate the expected value of the prediction and the interval of confidence and to guide the ANN selection process. Jia and Culver (2003) found it useful that the technique does not require separate available data in training and testing datasets, thereby avoiding the issue of selecting the optimal size for these datasets. Use of a maintenance of variance extensions (MOVEs) model aided the ANN in the flow generation when close to the training boundaries. Performance of the bootstrapped ANN model was successfully tested on the Buck Mountain Run case study.

Bowers and Shedrow (2000) used an ANN to predict the water quality variables in Mill Creek, a tributary of the Savannah River in South Carolina. A feed-forward ANN was trained to predict total suspended solids, total dissolved solids and total solids using precipitation, flow rates and turbidity measurements. Precipitation data used in the study was a USGS rain gauge in the studied watershed. The water quality training and validation dataset is composed of data measured during a 21-month period close to the Mill Creek watershed outlet. A coefficient of determination of 0.96 is calculated between the measured and predicted total suspended solids when the ANN is prediction only total suspended solids. On the other hand, when predicting total suspended solids, total dissolved solids, and total solids at the same time the coefficients of determination are 0.85, 0.94, and 0.95 respectively. The results showed a better performance of the ANN in predicting only total suspended solids.

Sandhu et al. (1999) develop an ANN to model the flow-salinity relationship with application to the Sacramento-San Joaquin Delta in California. The ANN was trained using historical measurements and the Delta Simulation Model 2 (DSM2), a 1-dimensional hydrodynamic and water quality model capable of simulating flow, stage, and water quality throughout the Delta. In this study, the explanatory variables for the ANN were river flows, canals gate positions, and diversions, including exports. Sandhu et al. (1999) explored different time steps to group the inputs variables and the concept of memory, including previous time steps values as inputs for the explanatory variables. They found that in using daily time steps there was less loss of information than for coarser time steps. In addition, they found that memory played an important role in the ANN predicted v. observed results showing significant improvements in the predictions when previous time step values where introduced. Unfortunately, limited statistical analysis of the errors was found in the literature reviewed. This ANN was intended to bring the detailed DSM2 water quality modeling results into CALSIM. Wilbur and Munevar (2001) reported a successful integration of the trained ANN into the CALSIM linear optimization solver by using a linearized constraint from the ANN salinity prediction. In one of the cases, the integral CALSIM-ANN Model allowed determination of reservoir releases to meet salinity requirements in the system.

Suen and Eheart (2003) applied ANN to predict Nitrate concentration in the Upper Sangamon River in Illinois, a typical Midwestern river. The explanatory variables used in this research were weekly cumulative precipitations, daily highest temperatures in three stations, daily streamflows, and the Julian date. The target values are daily Nitrate concentrations at a gauged point in the system. ANNs were compared with traditional methods such as multiple regression analysis (MRA) and the SWAT model, a mechanistic soil and water assessment tool (Arnold et al. 1996). In addition, the performance of radial basis neural nets and backpropagation neural nets was compared, showing preference for radial basis neural nets (RBNN)-based on production of more robust results and faster training. Prediction performance was analyzed based on accurately determining concentrations above or below the Nitrate concentration standard in the river. The false-negative and false-positive frequencies are used to estimate overall accuracy. The best overall accuracy corresponding to the RBNN was calculated between 78% and 83% for two different training scenarios. The overall accuracy was improved (86-89%) when training the ANN to predict a binary output.

Parkin et al. (2007) uses SHETRAN, an integrated watershed modeling system numerical model, to develop an ANN-based model to predict effects of groundwater abstractions in river systems in The United Kingdom. SHETRAN is a physically-based distributed modeling system for simulating water flow, sediment and contaminant transport in river basins (Ewen et al. 2000). It was chosen for this study due to its capabilities for representing integrated groundwater–surface water systems. SHETRAN provides the time-series and spatial variations in river flow depletion. The depletion curves are fitted from the SHETRAN simulations, thereby reducing the number of variables to predict. Two ANNs were applied in this study, with the first producing a binary output indicating wet conditions at the well, and the second generating model output to represent the depletion curve. The model predictions were tested with a unique field pumping experiment data set in the Winterbourne stream, UK that showed a predicted depletion curve with similar shape to the one found in the field experiment; Parkin et al. (2007) concludes that the similarity in the depletion curves from model with different parameters show the applicability of the model for realistic conditions modeling. This study demonstrates the successful application of a hybrid, numerical model-ANN, approach for modeling stream-aquifer interactions, and its potential for modeling more complex hydrological systems.

WATER QUALITY MODELING

Water quality relates to physical, chemical and biological characteristics of water. Salinity is a measure of the amount of salt dissolved in the water. Salts are substances such as "table salt" (sodium chloride, NaCl), limestone (calcium carbonate, CaCO3) and many others. They are picked up by the water as it runs over and through the rocks and soils of the basin. Low levels of these salts are vital to the growth of aquatic plants and animals but high levels can cause problems for aquatic life and for human uses such as crop irrigation. Modeling groundwater quality issues in irrigated river valleys has interested researchers for many years (Darton 1906; Austin and Colorado. Dept. of Public Health and Environment 1997; Bossong et al. 2000; Freiwald et al. 1988; Watts et al. 1992), and specifically salinity issues in irrigated land with significant reduction in crop yield (Miles et al. 1977; Gates et al. 2002).

Ground Water Quality in the Arkansas Valley

Gates et al. (2002) applied the GMS software package (Brigham Young University 1999) to model steady state groundwater flow and salt transport to a portion of the LARV in Colorado. GMS integrates MODFLOW for groundwater flow calculation and MT3DMS for conservative salt transport with a GIS-based interface for ease of defining the extensive spatial database requirements. The MODFLOW-MT3DMS model was developed to analyze and predict water table elevations and salinity and to simulate the interaction between the shallow aquifer, the river, and the irrigation-drainage system. This model includes a module to simulate the water quantity and quality in the unsaturated zone, and an improved module for drainage system improvements modeling. The model was calibrated based on extensive and detailed data collection effort. The finite difference model was applied using cells representing 6.25 ha, corresponding to roughly half the average field size in the region. The initially developed steady-state model has been further calibrated as a transient model over a 133 week period encompassing three consecutive irrigations seasons of data gathering from 1999 to 2001. The transient model provides an invaluable resource for understanding quantity and quality components of the stream-aquifer interaction and evaluating salinity control strategies (Burkhalter and Gates 2005, 2006).

Data collection has continued for six years, and in the near future it is expected that the transient model will be applied from 1999 to 2004. In addition, in the past five years the data gathering has been extended to an additional region downstream of the earlier modeled area. The same modeling schema will be applied to the downstream area. Some of the most outstanding features of the current transient finite difference model are: (1) an unsaturated zone model for water quantity and quality, (2) detailed evapo-transpiration calculation based on historical crop records and its dependency on the soil salinity, and (3) a module to include subsurface drainage modeling. The salinity and waterlogging control strategies that have been evaluated include: increases in well pumping rates, irrigation recharge reductions, seepage reductions, subsurface drainage, and combined strategies. Preliminary findings showed the most significant regional benefits by reducing excess recharge by increasing irrigation efficiency.

In-Stream Water Quality in the Arkansas Valley

Cain et al. (1987) studied the regression relationships of specific conductance to streamflow and major-ion concentrations for the surface water systems and groundwater systems of the Arkansas River Valley. Coefficients of determination (r^2) were reported that indicated adequate specific conductance predictions using streamflow. Relationships of specific conductance to the specific ions of calcium, magnesium, sodium, bicarbonate, sulfate and chloride concentrations were also developed for both surface and groundwater at various points along the river basin.

Lewis et al. (1998) studied relations between streamflow and specific conductance related to the reservoir operations in the LARV. The study examined the potential of changing the specific conductance and eventually the water use based on streamflow management. An analysis of the historical flows and changes in John Martin Reservoir operation was conducted before and after Pueblo Reservoir was built. Lewis et al. (1998) found seasonal changes in specific conductance due to mixing of seasonally-high specific conductance and seasonally-low specific conductance water in Pueblo Reservoir. The water mixing translated into an overall decrease in the median specific conductance value of the flow downstream of the reservoir. A general increase in the flows rate after Pueblo Reservoir was completed was also found, which was attributed to the winter storage program, increases in storage, and increased trans-mountain water used for irrigation. Downstream of John Martin Reservoir, the study found specific conductance decreasing significantly from September through April with no major changes during May through August.

Aquifer and Stream Water Quality in Colorado

Malone et al. (1979) developed a basin scale, stochastic steady-state model for water quality throughout the Colorado River basin using an existing model, SALT. The SALT model incorporated stochastic analysis by allowing in-stream salinity and the agricultural base leaching factor to be input as random variables. The agricultural base leaching factor represented an empirical value depicting the tons of salt removed from the soil per acre-foot of water flow through the soil matrix. SALT predicted the expected value and the variance for the natural salt load to the river.

Lee et al. (1993) developed a model primarily for economic policy analysis that considered natural flow variability in determining salt concentration. A set of differential equations were developed to describe the flow of total salts in the Colorado River basin. A steady state model was applied to simplify the number of equations required for the model, and was used to estimate the probability distribution of water quality improvement resulting from specific reductions in salt load or improvements due to different return flow salinity concentrations.

Riley and Jurinak (1979) proposed a concept to explain salt production in a natural watershed. The term *baseline salinity* was used to represent the natural release of salt from a watershed due to hydro-geochemical weathering within a basin. Data showed that the salt mass from a basin is relatively constant, meaning that the natural baseline salinity is relatively constant. Riley and Jurinak (1979) proposed two assumptions to develop the methodology. First, measured data were used to show that, generally, the amount of salt leached from the land is highest when it is first irrigated. It decreases as irrigation continues to what they named an "agricultural base salinity", which is constant. It was proposed that this concept could be applied to any basin once the land has been irrigated for many years, but no exact time frame was provided. Second, once the agricultural base salinity is reached, the salt loading is due only to a combination of the base weathering rate of the soil profile and to the underlying geologic formation. It was further proposed that when both of these assumptions are made, the removal of salt is directly proportional to the quantity of water passing through the soil profile. A relationship between irrigation efficiency and salt loading can be developed using the stated assumptions. Irrigation efficiency is a function of the total volume of water leaching through the soil profile.

Reservoir Water Quality Transport Modeling

Models, such as WQRSS (Smith et al. 1978), HEC-5Q (Hydrologic Engineering Center (U.S.) 1986;Willey et al. 1996), DYRESM (Hamilton and Schladow 1997), and HSPF (Bicknell and National Exposure Research Laboratory (U.S.) 2001), have been developed for water quality basin modeling but have serious limitations. The HEC-5Q (similar to

WQRSS and RESALT) and HSPF models incorporate a one-dimensional longitudinal river model with a one-dimensional vertical reservoir model (only one-dimensional in temperature and water quality and zero dimensional in hydrodynamics). DYRESM is another one dimensional hydrodynamic model with numerical descriptions of phytoplankton production, nutrient cycling, oxygen budget, and particle dynamics. Wells (2000b) introduces CE-QUAL-2E, a two-dimensional (longitudinal-vertical) water quality and hydrodynamic computer simulation model. This model improves previous versions by modeling of the vertical accelerations enhancing river-estuary, lake-river, and reservoir-river modeling. In general, modeling the complexity of the processes in the reservoir for different water quality components requires a large amount of input data. For example CE-QUAL-2E requires: bathymetry, meteorological data, inflows, inflow temperatures, inflow constituent concentrations, tributary inflows, tributary inflow temperatures, tributary inflow constituent concentrations, upstream head elevations, upstream head boundary temperatures, upstream head boundary constituent concentrations, downstream head elevations, downstream head boundary temperatures, downstream head boundary constituent concentrations, outflows, light extinction, withdrawals, vertical profile at dam for specifying initial conditions, longitudinal and vertical profiles specifying initial conditions for each cell, wind sheltering, solar radiation shading, and gate flows/operation.

ANN has been successfully applied to model water quality (eutrophication) in reservoirs around the world. Karul et al. (1999) designs an ANN-based methodology for eutrophication lake management. Karul et al. (2000) trained an ANN to predict Chlorophyll-a concentration variations in four Turkish water bodies as a function of PO4, NO3, alkalinity, suspended solids concentration, pH, water temperature, electrical conductivity, dissolved oxygen, Secchi depth, density of Daphnia species only, and bulk densities of species belonging to Cladocera and Copepoda. In the same line, Walter et al. (2001) predicted Chlorophyll-a in an Australian reservoir. Walter trained the ANN to forecast magnitude of algal biomass in short term (7 days) ahead for early warning and tactical control.

CHAPTER 3

RIVER GEODSS: COMPONENTS AND MODULES

River GeoDSS is developed to provide the user with a powerful interface and seamless integration of its components for conjunctive use groundwater-surface water quantity and quality river basin modeling. The powerful ESRI®-ArcMap™ spatial interface is selected to provide the framework for the *River GeoDSS* user to enter and manage data, operate the DSS, display results and perform analysis. Most of the existing decision support tools lack geo-referenced integrated interfaces (e.g., AQUATOOL (Andreu et al. 1996), WRAP (Wurbs 2005), RiverWare (Zagona et al. 2001)), giving the *River GeoDSS* design a distinct advantage over these models. Embedding the *River GeoDSS* in a popular and well accepted GIS interface facilitates adoption of the tool since potential users might already be familiar with the interface, and not having to learn a new interface is attractive to the user. In addition, the *River GeoDSS* is packaged with tools and interfaces that allow both experienced and inexperienced users access to the modeling system for performing analysis and answering management and improvement questions with minimal user-required manipulation of data and modeling procedures (e.g., network transformations and calibration/simulation modeling structures). Most of the procedures required to calibrate/simulate a basin in *River GeoDSS* are included in its set of tools, thereby minimizing manual data processing and setup of the system models and modules.

GENERAL *RIVER GEODSS* STRUCTURE

The *River GeoDSS* structure is conceived as centered around a geo-referenced-spatio-temporal database, where river basin data are spatially-managed utilizing GIS capabilities in an object-oriented fashion. The *River GeoDSS* is developed as an integration of graphical components, models, databases, and processing tools with programming code linking all the components together. The *River GeoDSS* contains interfaces to connect models and modules with the database, and graphical user interfaces to facilitate selection of preferences and data manipulation, minimize manual processing tasks and reduce errors when processing large amounts of data. The main components of the *River GeoDSS* are: (1) computer software such as: ArcGIS™, MODSIM, MODFLOW, MT3DMS and MATLAB®, and (2) two modules for water quality modeling and ANN training and integration support. Figure 3.1 shows the *River GeoDSS* components and their interaction within the *River GeoDSS*. The spatial-temporal database contains all the relevant system information and measured data, and he GIS framework displays data, hosts interfaces for data input/output, and delivers a robust spatial processing environment. The MODFLOW-MT3DMS models provide accurate, physically-based groundwater quantity and quality modeling, and ESRI-ArcObjects and SQL encapsulated in VB.NET code customized data processing. Geo-MODSIM, as implemented in the ArcMap interface to ArcGIS, offers the powerful network flow modeling environment which is enhanced with optional (1) ANN stream-aquifer interaction modeling, (2) ANN reservoir water quality transport modeling, and (3) conservative surface water quality routing. The *River GeoDSS* modules are dynamically linked in the Geo-MODSIM modeling environment to provide fully integrated river basin simulation.

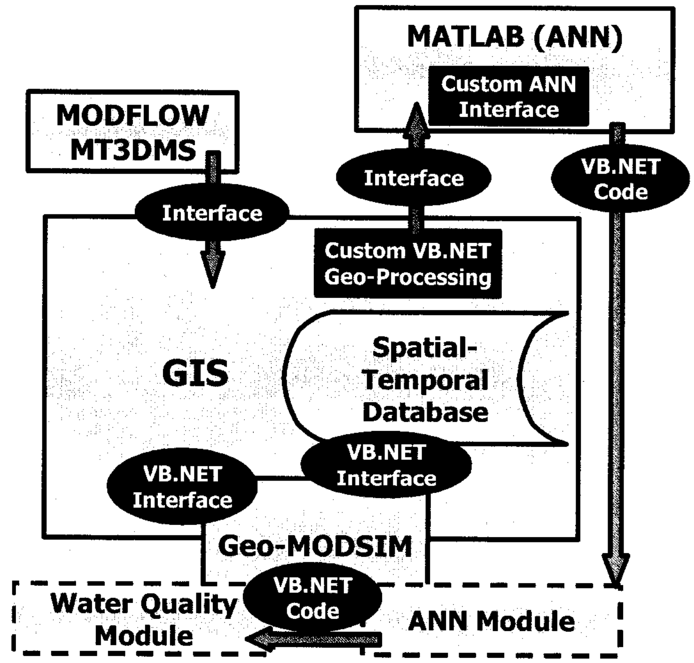

Figure 3.1 – DSS structure diagram

The *River GeoDSS* implements the *Extension* concept to enable/disable optional modules and sets of customized tools that enhance the *River GeoDSS* capabilities in an application-specific fashion. The extensions allow efficient loading of components and data in memory, faster access to data stored in memory, and customized user interfaces that display only active component options and case-specific tools. The extensions are accessed form the main menu under *River GeoDSS Extensions* (Figure 3.2). The Water Quality Module (WQM) and Geo-MODFLOW are available as extensions, with the WQM extension enabling various *River GeoDSS* water quality and file management tools (e.g., loading and saving data within the *River GeoDSS* project). Geo-MODFLOW, as an extension, enables tools for integration of surface water and groundwater modeling. Specialized extensions specifically for the Arkansas River basin provide access to the customized user interfaces and tools that allow case-specific data import and handling, as well as custom run types.

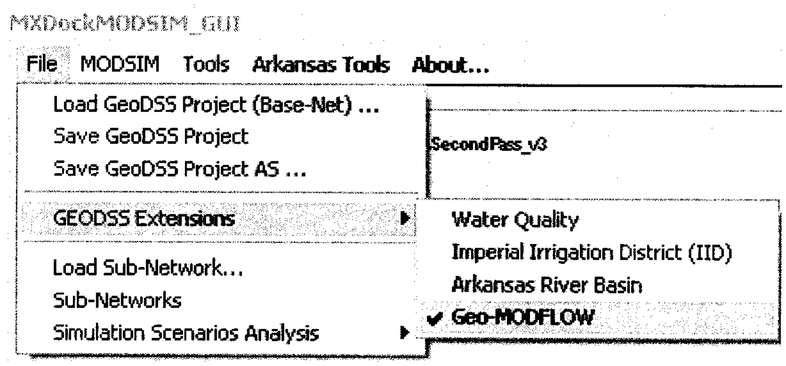

Figure 3.2 – *River GeoDSS* extension menus

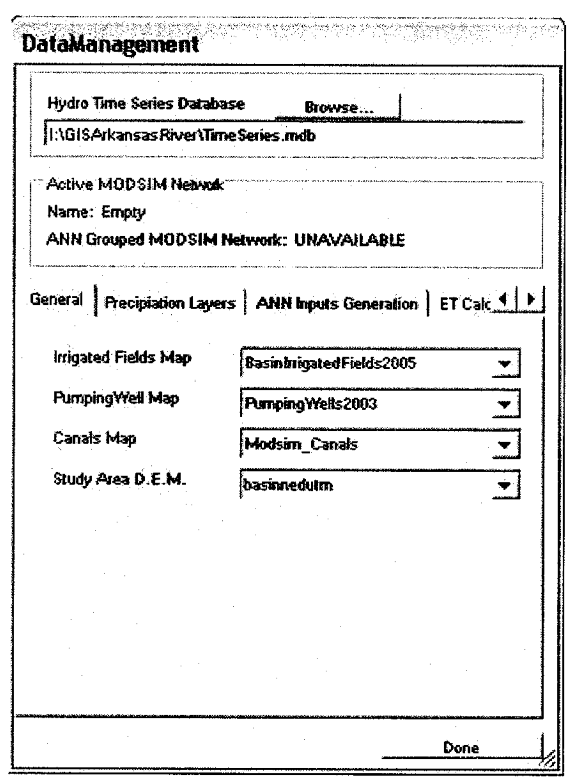

Figure 3.3 – *River GeoDSS* Data Management Interface

A Data Management Interface is implemented in the *River GeoDSS* for organizating layers and files for all components and modules. The *River GeoDSS* Data Management Interface allows setting: (1) the time series database file, (2) water quality database file, (3) precipitation raster map locations, (4) the ANN buffers database file, (5) the ANN training database file, (6) precipitation summary database file, (7) the feature class names for irrigated fields, pumping wells, canals, streams, DEM layer, water bodies, and (8) the MODFLOW finite diference grid, and polygon feature classes representing the extent groundwater modeled area and user defined grouping areas for stream-aquifer modeling using ANNs. Figure 3.3 shows the general tab of the *River GeoDSS* Data Management Interface.

GEO-MODSIM

The geo-referenced version of MODSIM called Geo-MODSIM is developed to combine the advantages of spatial distributed information and MODSIM network flow modeling. Geo-MODSIM is implemented as an extension in ArcGIS™ 9 (ESRI®, Inc.) to apply MODSIM to geo-referenced basin models using the ESRI geometric network utilities to create, edit and display the network. The ArcMap™ interface for ArcGIS serves as a geo-referenced user interface for MODSIM, allowing advanced network display and access to network objects. In this way, Geo-MODSIM allows full utilization of the available spatial data processing, display, and analysis tools available in ArcGIS™, in conjunction with the powerful MODSIM model functionality.

A GIS geometric network is a "single dimension non-planar graph with features where edge elements and junction elements are connected by topology" (Borchert 2003) or simply a set of connected edges and junctions for which the GIS knows how things are connected from point A to point B (including flow direction). The MODSIM network is composed of nodes (i.e., reservoirs, demands and non-storage nodes) connected by one-directional links. The similarities between the GIS geometric network and a MODSIM network allow Geo-MODSIM to use the geometric network as the MODSIM network. Using MODSIM v8 .NET integration and ESRI-ArcObjects, Geo-MODSIM packs a set of tools to link geo-referenced system objects in GIS and the model objects. The MODSIM object oriented database is well suited to the linkage structure associated with geo-referenced objects.

Geo-MODSIM Data Model

ESRI geo-database feature classes are used as data sources to define the geometric network. A data-model is developed as template to create the river basin features in ArcGIS and facilitate the building of the MODSIM network in Geo-MODSIM. Figure 3.4 shows the GIS data-model structure; detailed description of the feature classes and fields is found in the *River GeoDSS* User Support (Appendix III).

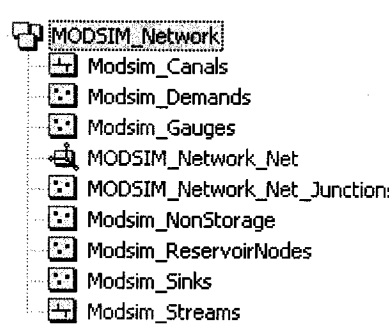

Figure 3.4 - Geo-MODSIM data-model in ArcCatalog™

Geo-MODSIM geometric network

When a geometric network is created, ArcGIS also creates the corresponding logical network, which is used to represent and model connectivity relationships between features.

The logical network is the connectivity graph used for tracing and flow calculations. The MODSIM network topology is constructed directly from the ArcGIS™ logical network. Geometric network nodes are used to create the system nodes and the logical network connectivity is used to create the links between nodes in MODSIM. A set of supporting (synchronization) tables are generated in the geo-database during the MODSIM network creation process. Detailed description of these tables is found in Appendix III.

The geometric network uses six types of nodes: Gauges, Demands, Reservoir, Sinks, Non-storage, and network junctions. In addition, the geometric network implements two types of links: Streams and Canals. These geo-referenced objects are transformed into MODSIM objects while building the MODSIM network. Demands, Reservoirs, Sinks and Non-Storage nodes are common to both the geometric network and the MODSIM network and network junctions are implemented as non-storage nodes. The Gauges nodes are implemented as *flow-through* demand nodes, which are capable of routing non-consumptive water to a downstream node. Base network non-storage nodes defined as interfaces, connecting end of canals with the stream system, are transformed into *flow-through* demands, allowing modeling of operational flow returns to the system.

A common practice is to begin the creation of the geometric network by importing the National Hydrologic Dataset (NHD) stream and canal layers, reservoirs, gauging stations, diversion structures, and wells into the data-model feature classes. Network Utility analyst available in ArcGIS provides tools to test connectivity and adequately implement water movement in the network (e.g., find connected nodes and links, trace up/downstream, find disconnected nodes and links, etc…).

Geo-MODSIM tools in ArcMap

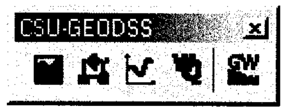

Figure 3.5 – GeoDSS Toolbar in ArcGIS

Geo-MODSIM tools are accessible from the *River GeoDSS* toolbar in ArcGIS (Figure 3.5). The Geo-MODSIM main dialog ( ) gives access to standard MODSIM settings and dialogs (Figure 3.6). The main dialog accesses tools for (1) creating the MODSIM network from the active geometric network in the ArcMap™ project, (2) loading and saving the corresponding MODSIM xy file where the network is stored, (3) accessing MODSIM menu items (Figure 3.6), and (4) invoking basic network synchronization tools. The MODSIM menu items provide access to MODSIM network settings, the water rights dialog, output control, MODSIM extensions, network cost overview and utilities for spatial model output results display. The MODSIM network basic execution is triggered in this dialog.

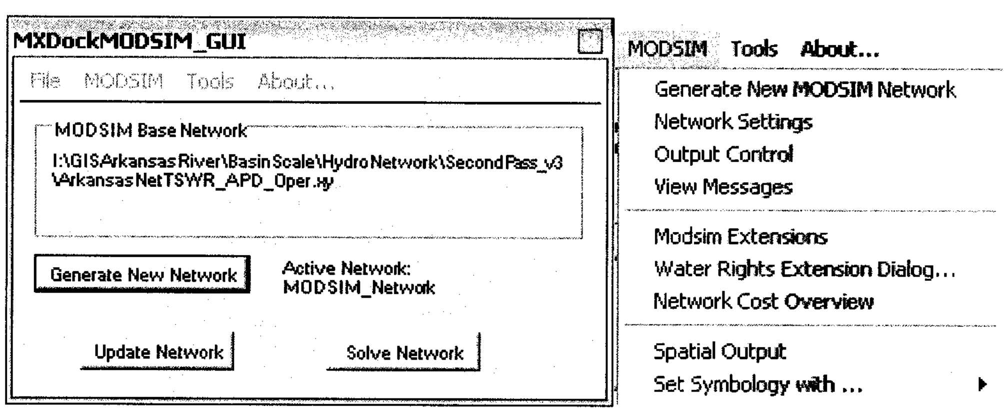

Figure 3.6 – Geo-MODSIM main interface and menu items in ArcMap™

The Geo-MODSIM *Select Feature Tool* ( ) displays the MODSIM database entry dialogs associated with the network objects. Figure 3.7 shows the MODSIM dialog displayed by clicking a system demand node with mouse pointer using the Geo-MODSIM *Select Feature Tool.*

The Geo-MODSIM *Output Tool* () triggers the standard MODSIM output display interface for the selected network object. The output consists of tables and time series plots of the modeled values for all time steps. Figure 3.8 shows an example time series plot for a demand node in the system.

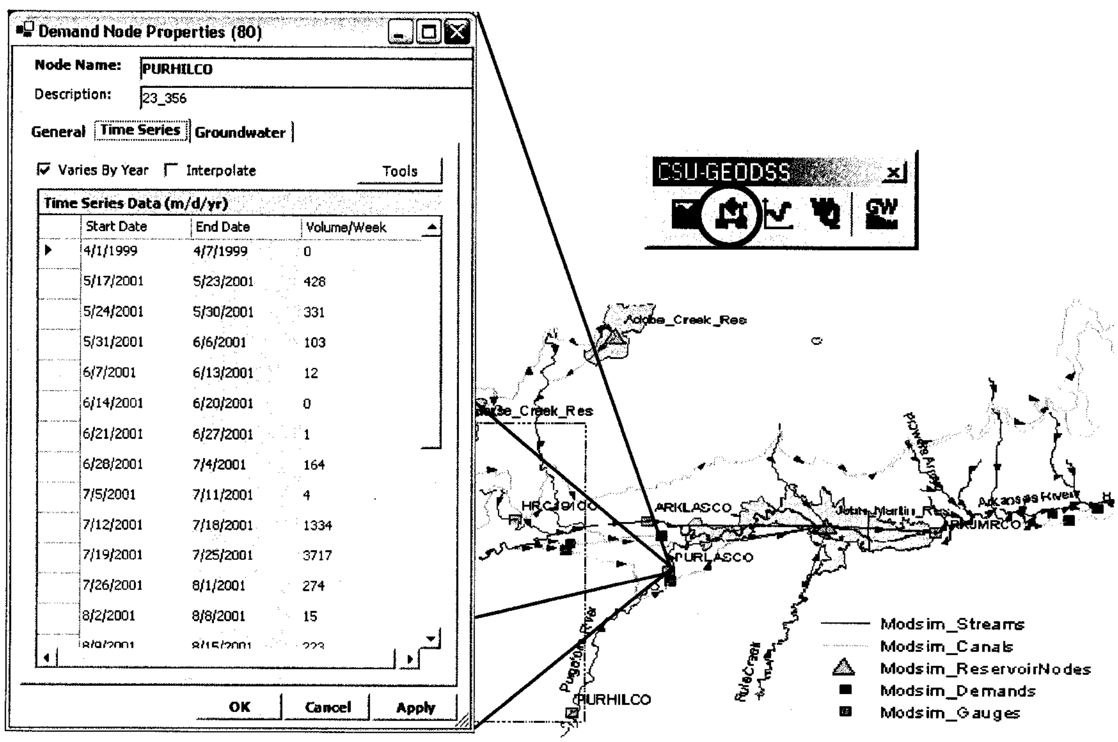

Figure 3.7 – Geo-MODSIM select features tool in ArcMap™

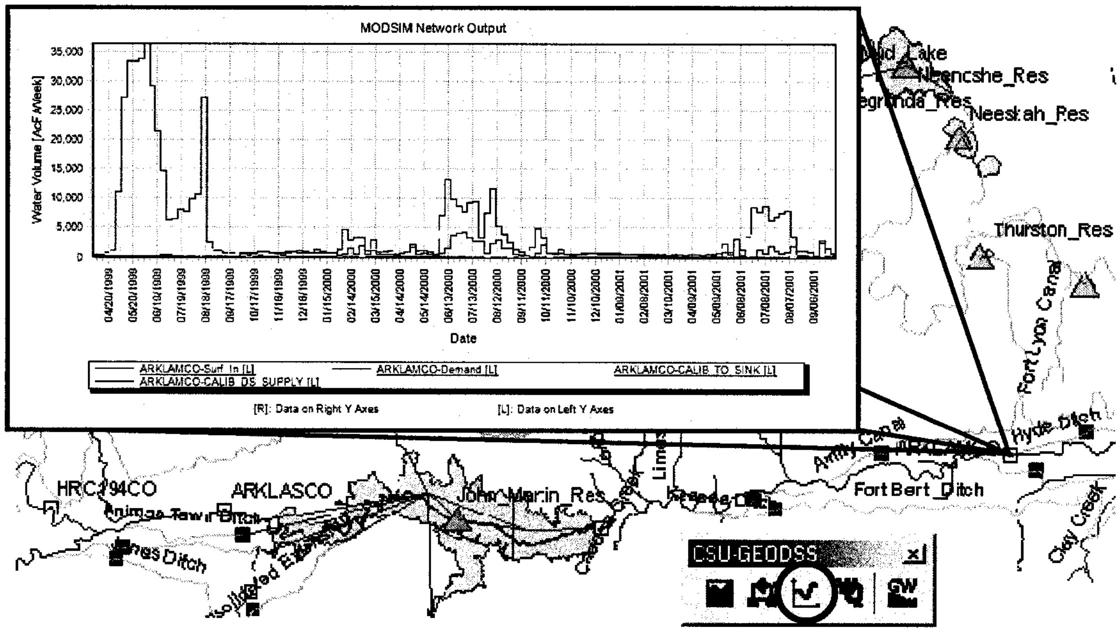

Figure 3.8 – Geo-MODSIM Output Display Tool in ArcMap™

Data-model Data Transfer

System data can be stored directly in the geo-database and loaded into the MODSIM network for model execution without having to maintain the data in both MODSIM and GIS. Data that can be stored in the geo-database include: reservoir capacities, link costs, node priorities, link capacities, and channel loss coefficients.

Network Types in Geo-MODSIM

The MODSIM network created from the geometric network is stored as the Geo-MODSIM *Base-Network*, a MODSIM native xy file. The *Base-Network* is used in Geo-MODSIM to create both calibration and simulation networks. At run time, according to the run type specified (i.e., calibration or simulation), and the active simulation scenario, the network structure is modified, functional structures added and data loaded into another MODSIM file called *Sub-Network*. The Sub-Network MODSIM file is named after the Base-

Network suffixed with the simulation scenario name. Sub-Networks can be turned into an active Geo-MODSIM network (for input/output) using the *File→Sub-Networks* menu item. Sub-Networks generated/executed in *River GeoDSS* are made available to the user for display and comparative analysis under its simulation scenario name. The *River GeoDSS* interface provides tools for comparing side-by-side simulation scenario results under the *Sub-Networks Analysis* menu item by clicking the check boxed next to the available Sub-Networks to be included in the output comparison. The Base-Network and Sub-Networks share the same GIS topology; however, the data can be different (e.g., diversions, channel losses, costs, priorities, etc…). Additional Sub-Networks created in a different *River GeoDSS* project can be loaded into Geo-MODSIM using the menu items. Simulation of changes to the system topology requires generation of a new Base-Network, but the network cannot be categorized as a Sub-Network. Figure 3.9 shows a diagram of the GIS geometric networks and MODSIM Base and Sub-Networks.

The Base-Network can be initially loaded with data that will be used in all Sub-Networks. In some *River GeoDSS* applications, a customized run is implemented to dynamically import time series and other data at run time for each simulation. The latter alternative does not require maintaining the time series in the MODSIM file; rather, the series can be loaded from a central location (e.g., a database). In cases where time series are the same for the simulation scenarios, it is convenient and efficient to store them directly in the MODSIM database.

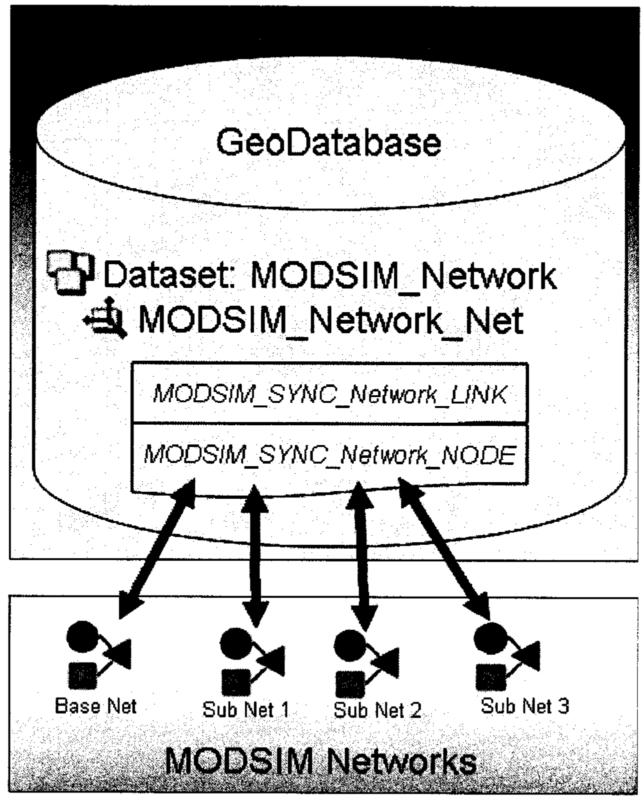

Figure 3.9 – Geometric network and MODSIM network interaction diagram

ANN MODULE IN *RIVER GEODSS*

River GeoDSS ANN module consists of a set of tools to conduct ANN-assisted modeling of river basin systems and integrate the ANN predictions within other components of the decision support tool. The module provides support for neural network training dataset creation and simulation. The module uses ESRI-ArcObjects libraries to build spatially grouped training datasets. The ANN module uses custom MATLAB exported files to load trained neural networks into the *River GeoDSS* to perform simulations, where the export files are generated by the *ANN MATLAB Export Tool.* In simulation, explanatory variables are dynamically generated for each modeling time step. Four types of neural networks are currently supported in the ANN module: Feed forward back propagation (including

Cascade Forward Network), Elman neural network, Radial Basis Neural Net and Generalized Regression neural network.

Special Considerations on the ANN Simulation in River GeoDSS

The ANN simulation dataset needs to be consistent with the training dataset to guarantee accuracy in the predictions; i.e., the basin system states assumed for training based on the groundwater simulations should be dynamically duplicated while simulating them in the *River GeoDSS*. During simulation, the *River GeoDSS* implements the option to generate the ANN simulation datasets from the current MODSIM modeled variables, assuming the explanatory variables are updated each iteration. Although the simulation dataset is generated in a similar fashion to the training dataset, explanatory variables that are functions of the modeling variables might change considerably between simulation and training. It was found in this study that this option creates instability with a slow and inconsistent convergence. In addition, there is a risk of creating an ANN simulation dataset with a different variable space than the dataset used for training, thereby increasing the prediction uncertainty and reducing the overall accuracy of the prediction by accumulation of errors.

An option to support usage of previous runs is implemented by creating a set of explanatory variables that depend on modeling variables from a previous simulation solution. For each time step, the modeled variables, such as river flow, canal diversion, aquifer recharge, and canal seepage, are extracted from the previous simulation results. The advantage of this option is that the previous simulation run is based on a calibrated network that can include complex operations and previously calculated return flows without the need for simplifications. Therefore, the ANN simulation dataset can include complex modeling elements without directly using the current simulation variables that create instability and convergence issues. The previous simulation support option, at the beginning of the simulation, creates a copy of the existing MODSIM output file for the network that is being simulated. This copy of the output file is used to query the system variables in order to build the ANN explanatory variables. An iterative ANN training-simulation process allows refining the ANN performance by reducing the variability of complex explanatory variables such as river flows and diversions resulting from simulation predicated on the ANN predicted flows and water availability.

ANN MATLAB Export Tool

A tool to export the MATLAB trained ANN is implemented for the *River GeoDSS*. The tool extracts required information from the training process and the MATLAB trained ANN for external simulation. The exported text files include input/output scaling parameters, network structure and configuration; and all associated connection weights and biases. Using these exported files, *River GeoDSS* is able to perform ANN predictions when a set of explanatory variables is presented. Detailed descriptions of the files structures and contents are provided in Appendix III – *ANN Modeling Files in River GeoDSS*.

ANN Priming

As found in the literature, and corroborated by earlier experimentation with ANNs, the outputs from previous time steps provide a system "memory" that can significantly improve prediction accuracy. During simulation, the ANN module uses previous predictions to generate the simulation dataset, but for the initial time steps in the simulation, there are no previous predictions to use as explanatory variables. Therefore, the sequential predictions use previous predictions that contain errors. It was observed that the previous output explanatory variables in the first stages of the simulation greatly influence the entire simulation prediction space. That is, when the initial errors are large, the ANN is unable to recover from these errors and the predictions deteriorate over the remainder of the simulation. A priming procedure is implemented in the ANN module to improve selection of the starting explanatory variables. Prediction over initial time steps are iteratively repeated until the prediction converges within a tolerance range. The algorithm predicts the first time step using averages of the explanatory variables in place of use of the previous predictions. The generated prediction then replaces the averages. Since the prediction was calculated using all other actual explanatory variables for the first time step, the process is expected to move the prediction towards a "better" system state at the beginning of the simulation. An iterative process is implemented in which the explanatory variables from previous time steps are replaced with the previous iteration prediction until the prediction converges to a value within 10% of the previous prediction (a maximum of 3000 iteration are allowed). This prediction becomes the output for the first time step, which is then used for the next time step prediction as the *(t-1)* previous output. This process is repeated for all initial time steps where the previous outputs are unknown, where the number time steps to prime depends on the number of previous time steps that the neural network relies on. Figure 3.10 illustrates the most important element of the ANN priming procedure.

ANN Radial Basis Prediction in River GeoDSS

Unrealistic predictions outside the training areas might be possible when explanatory variables found in the variable space differ significantly from those in the training space. The radial basis NN predictions are constrained in the *River GeoDSS* to a range around the maximum and minimum values observed in training, thereby maintaining realism of the predictions. The prediction range is set as a percent of the training range between the maximum and the minimum values, and is calculated as:

$$\begin{aligned} n\_Max_i &= Max_i + d_i \\ n\_Min_i &= Min_i - d_i \end{aligned} \tag{3.1}$$

where Max_i is the maximum training value for output variable *i*; Min_i is the minimum training value for the output variable *i*; n_Max_i is the upper bound on the prediction space for output variable *i*; n_Min_i is the lower bound on the output *i* prediction space; and *d* is the deviation above the training maximum and below the training minimum to compute the prediction range, where *d* is computed as a fraction (*F*) of the original range.

$$d_i = \frac{F \cdot (Max_i - Min_i)}{2} \tag{3.2}$$

The ANN predictions in the *River GeoDSS* are calculated with a factor of $F=0.25$, allowing a 25% wider prediction range.

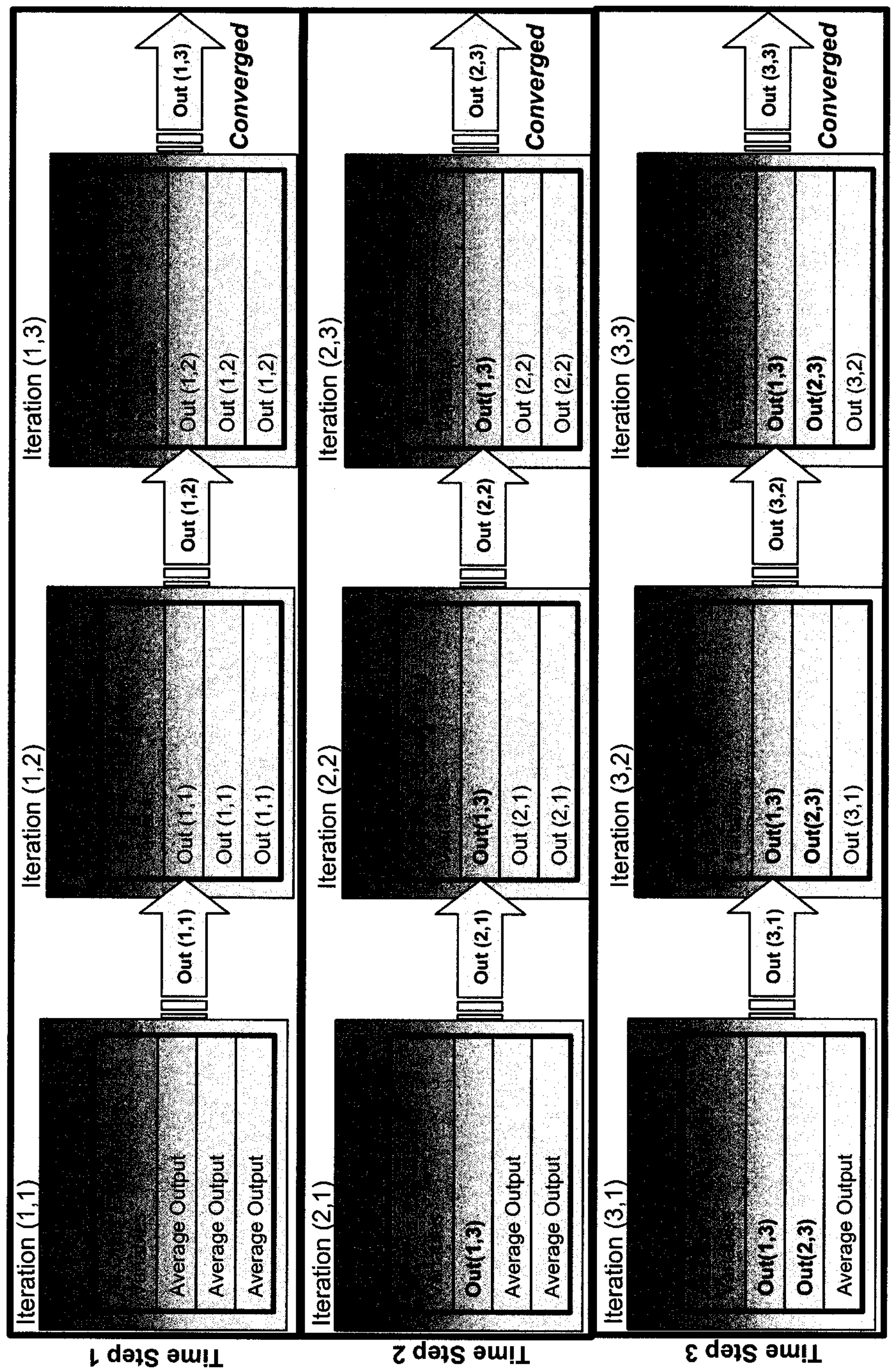

Figure 3.10 – Neural network Priming Procedure Diagram

WATER QUALITY MODULE

A Water Quality Module (WQM) is developed to route conservative water quality constituents throughout the system that is coupled with the Geo-MODSIM network flow solution at each time step. The WQM introduces a generalized algorithm to trace the MODSIM network from upstream to downstream in the correct sequence, allowing calculation of concentrations at any point in the network based on previously calculated concentrations on upstream links. The network tracing algorithm is made available through the MODSIM network utility library, as part of the MODSIM version 8 standard package.

For each time step, network concentrations are calculated after the MODSIM network flows have converged to a solution. The MODSIM flow solution is combined with known concentrations to route the resulting constituent mass downstream using the mass conservation principle at the network nodes. The one dimensional mass conservation principle applied to a control volume in the network is expressed as:

$$\frac{\partial \dot{m}}{\partial x}dx \pm R_{source/\sin k} = -\frac{\partial m_{box}}{\partial t} \tag{3.3}$$

where $\dot{m}$ is the flux through the control surfaces; water constituent flux is $\dot{m} = C\,Q$, where C is concentration and the flow rate Q = velocity ($\bar{v}$) in the x direction times the cross sectional area; R = loading rates for sources or sinks; and $m_{box} = VC$ = mass in the control volume, where V= volume of the control volume. Therefore,

$$\frac{\partial(C \cdot \bar{v}dydz)}{\partial x}dx \pm R_{source/\sin k} = -\frac{\partial(C \cdot dxdydz)}{\partial t} \tag{3.4}$$

$$\frac{\partial(C\bar{v})}{\partial x} \pm \left(R/V\right)_{source/\sin k} = -\frac{\partial C}{\partial t} \tag{3.5}$$

The general advection-diffusion transport equation may be written as:

$$C\frac{\partial \bar{v}}{\partial x}+\bar{v}\frac{\partial C}{\partial x}\pm C_{source/\sin k}=-\frac{\partial C}{\partial t} \tag{3.6}$$

Neglecting diffusion and assuming a conservative constituent, i.e., assuming no change in concentration in the x direction and no change in concentration over time:

$$\dot{m}_{out}-\dot{m}_{in}\pm R_{source/\sin k}=0 \tag{3.7}$$

where $\dot{m}_{out}$ = mass rate out of the control volume and $\dot{m}_{in}$ = mass rate entering the control volume. Equation 3.7 can be written for any node in the network as:

$$\sum C_{out}Q_{out}-\sum C_{in}Q_{in}=0 \tag{3.8}$$

Equation 3.7 implies complete mixing at the system nodes to model the water constituents. Since only network nodes, and not network link elements, are assumed to have external sources or sinks, the rate of mass entering a link upstream is equal to the rate of mass leaving the link downstream. Concentration calculations at the nodes are performed sequentially, starting at the most upstream nodes in the system, in the order dictated by the network tracing algorithm. The sequential calculation computes outflow link concentrations at each node as a function of the inflow links.

$$C_{out}=\frac{\sum_{in} C_i Q_i}{\sum_{out} Q_i} \tag{3.9}$$

Figure 3.11 shows a basic diagram of the WQM and MODSIM coupling. The WQM implements an MS-Access database to store the module parameters and data for each *River GeoDSS* project. During simulation, the module reads the network node inflow concentrations and calibration tolerances from the MS-Access database. When the MODSIM network is initialized, the network is traced and the node order from upstream to downstream is established. Once a solution for a time step is achieved in MODSIM, the module calculates water constituent concentrations throughout the network. The concentration of water flowing out of a node is a function of the concentration of all sources of water flowing into that node. The WQM is integrated with the *River GeoDSS* ANN module to include ANN prediction in the computations (e.g., groundwater-surface water quality integration and reservoir water quality transport). When a trained ANN is available, the WQM uses the ANN groundwater constituent load predictions as external contributions to the nodes.

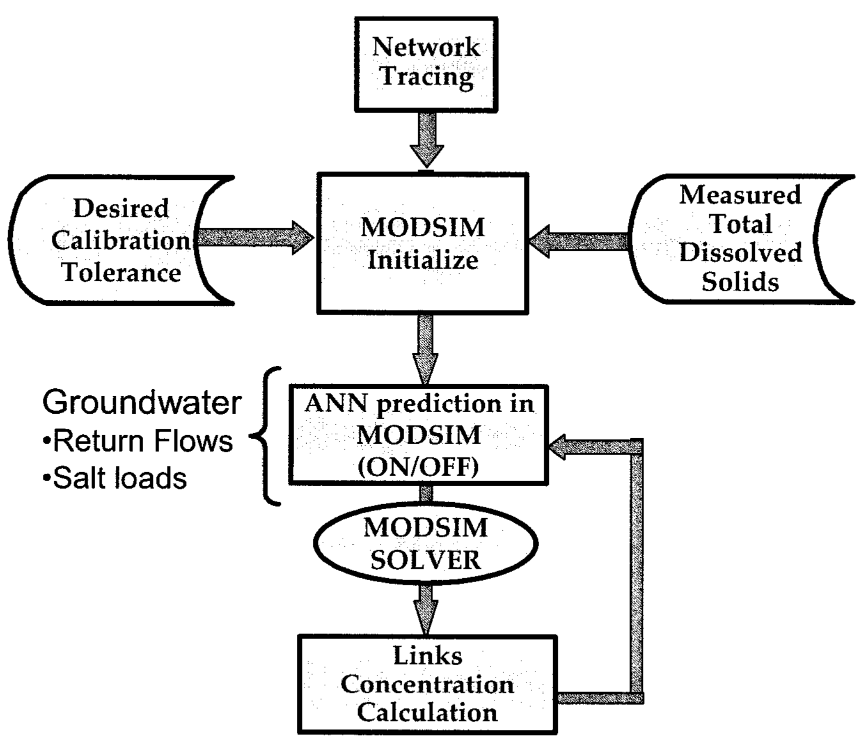

Figure 3.11 – Water Quality Module and MODSIM coupling diagram

Water Quality Module User Interfaces

A set of interfaces are implemented in the WQM to interact with the user. The interfaces allow (1) entering, editing and visualizing water quality input data (Figure 3.12), (2) developing and incorporating in the modeling the concentration vs. flow relationship (Figure 3.13), (3) the setting upper and lower bounds for water quality model calibration based on historical measured values (Figure 3.14-A) and (4) import of time series data from the water quality database for the WQM (Figure 3.14-B).

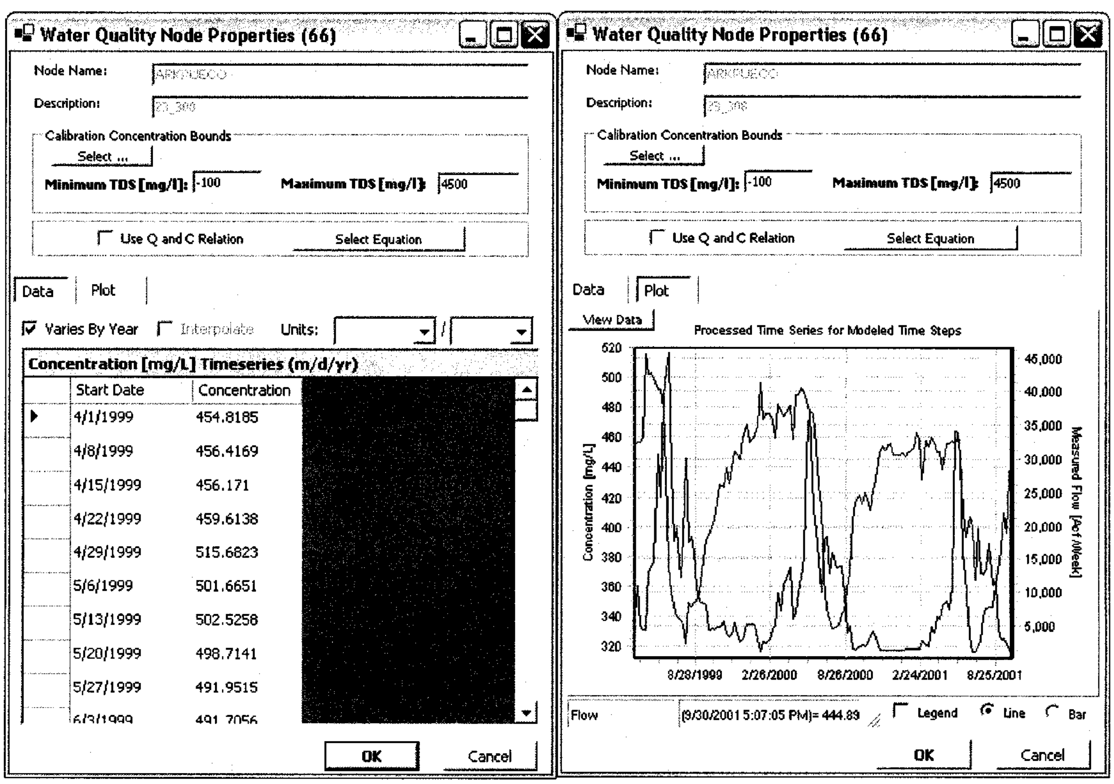

Figure 3.12 – WQM network node user input dialog sample

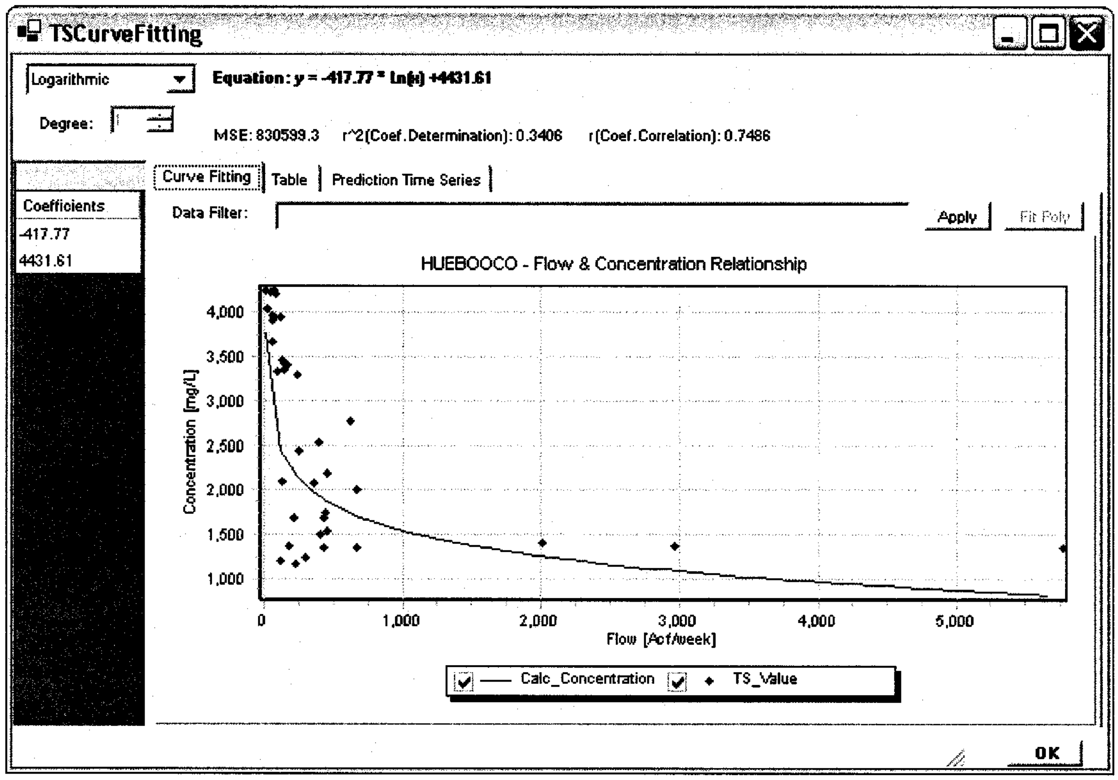

Figure 3.13 – WQM Flow-Concentration relationship user dialog sample

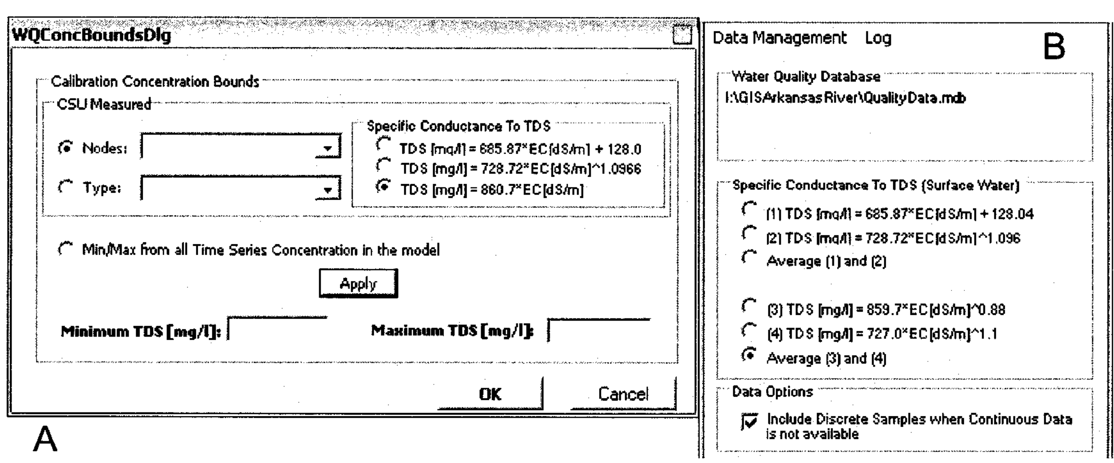

Figure 3.14 – Water Quality modeling preferences and WQ data import user dialog samples

Water Quality Data in WQM

Measured concentrations are imported and processed to be consistent with the simulation time step. Data are usually made available as daily mean concentration, use of larger simulation time steps requires processing of the concentration data. Processed data are stored in a customized MS-Access database associated with the Base-Network name. The imported data are represented in the *River GeoDSS* as a MODSIM style time series (Figure 3.12), where the missing data are filled with the available previous value. Additionally, the available data can be used to fit a regression equation to the available points (Figure 3.13). Basic functionality for polynomial equation regression is provided in the interface, where user defined equations of other types (e.g., exponential, power, logarithmic) can be externally processed and entered using the equation coefficients spreadsheet. When using a regression equation at a gauging station, the equation is used in the WQM to represent the water quality constituent for all time steps as a function of flow. The interface shown in Figure 3.13 allows filtering of the data and provides plots of measured and calculated concentrations and flows. The regression equation preferences are stored in the *River GeoDSS* project Water Quality Database. Description of the data import tool is found in Appendix III – *RIVER GEODSS Water Quality Import Tool*, and details of the structure and characteristics of the WMQ database are found in Appendix IV – *Water Quality Database*.

Network Tracing

The WQM features an efficient network flow tracing algorithm that allows navigating throughout the fully circulating MODSIM network from the physical upstream nodes to the downstream nodes. The network tracing algorithm creates a logical order to calculate mass balance at the system nodes. Details on the tracing algorithm are given in Appendix IV – *Network Tracing Algorithm.*

Water Quality Module Results in River GeoDSS

Combined with the simulated flow results, the user is able, at any location in the system (e.g., river, canals and network nodes), to monitor constituent concentrations. A MODSIM user-defined output is implemented to graphically display concentrations at links and nodes. For nodes, graphs are provided for (1) the concentration at that point in the system as result of the combined concentrations and flows of links flowing into that node and (2) the measured concentration at the system nodes. The WQM output is then embedded in the MODSIM output database and made available to the user through the standard MODSIM output tools. Figure 3.15 shows a sample of the modeled/measured concentration results as displayed in ArcMap™ using the Geo-MODSIM output display tool for a station in the Arkansas River.

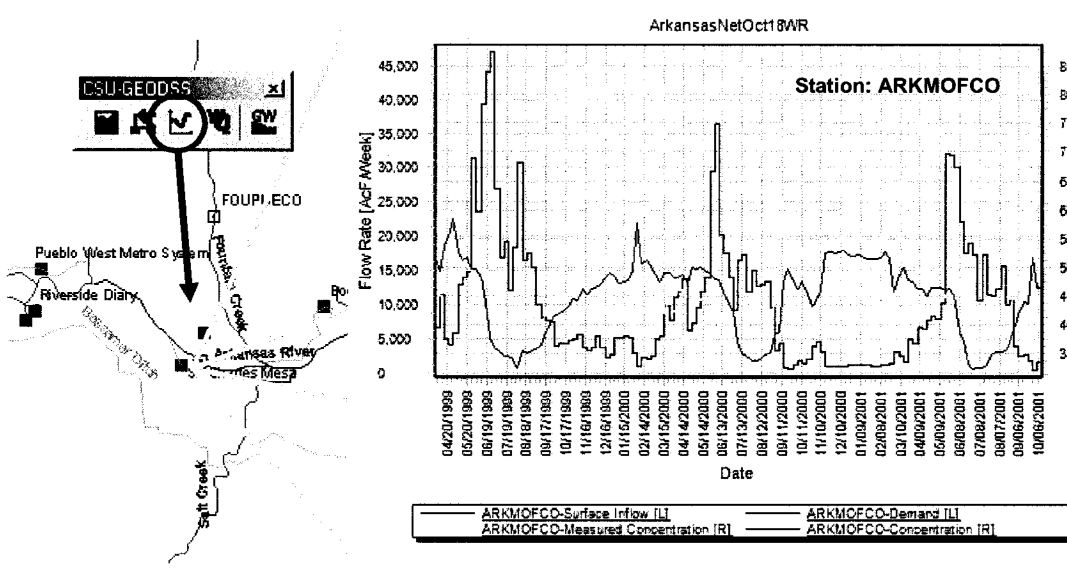

Figure 3.15 – Water Quality results display in *River GeoDSS* example

Simulation Scenarios Manager

This tool allows the user to create, edit and delete simulation scenarios in the *River GeoDSS*; and to select the active scenario for *River GeoDSS* modeling. Each simulation scenario network is constructed from the Base-Network, with containing modeling options such as: (1) quality module activation, (2) stream-aquifer interaction module activation and preferences, (3) run types, and (4) calibration options. Sub-Networks created in this manager are automatically made available in the scenarios analysis module when the *River GeoDSS* project is loaded. Simulation scenario information is then stored in the geometric network geo-database so as to be available as part of the *River GeoDSS* project.

Geo-MODFLOW

River GeoDSS features the Geo-MODFLOW extension as a set of tools that allow querying of the MODFLOW-MT3DMS binary output files based on the geo-referenced model grid in ArcGIS. An ArcMap VBA macro is implemented to create the geo-referenced MODFLOW grid layer in ArcMap. The macro uses the GMS file **.2dg* to extract the cell coordinates and creates polygons to represent the model cells. The field *CellNumber* is populated with the MODFLOW first layer cell number providing linkage between the output files and the geo-referenced cell object. The MODFLOW-MT3DMS output is processed using spatial relationships between the grid cells and other features in the GIS (e.g., MODSIM nodes or links, groundwater modeling grouping areas, and area-buffers). The tool allows summarizing, by geographic features, the elements of the MODFLOW flow budget (Sources and Sinks - Figure 3.16) and MT3DMS concentrations.

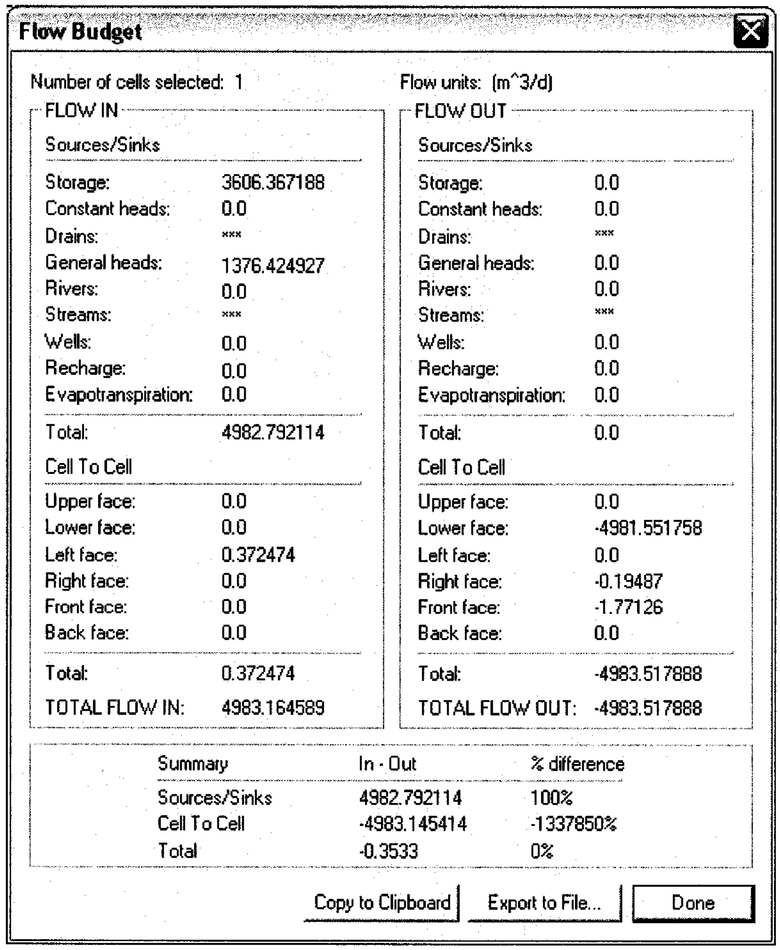

Figure 3.16 – MODFLOW Flow budget in GMS (Environmental Modeling Systems, Inc)

The Geo-MODFLOW *Select Tool* () is available from the *River GeoDSS* tool bar, allowing selection of any single feature in GIS for which Geo-MODFLOW processes and summarizes the MODFLOW-MT3DMS output. In addition, Geo-MODFLOW provides a user interface (Figure 3.17) that allows (1) selecting the component of the flow budget (Figure 3.16) to be summarized, (2) generating combined flow budget summaries for feature(s) currently selected in ArcMap, and (3) specifying the type of spatial relationship between the selected feature(s) and the groundwater model grid. The interface implements six spatial relations between the grid and the GIS features: intersects, overlaps, touches, contains, crosses and within. The user interface is displayed during the loading of the active scenario MODFLOW output files in memory or when the *select tool* is activated.

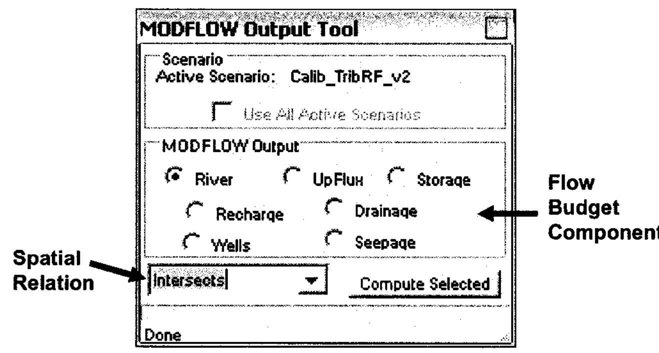

Figure 3.17 – Geo-MODFLOW user interface as displayed in ArcMap™

This tool generates a summary that contains a plot and a table with all summations for all modeled time steps of the selected flow budget component for all the cells that meet the specified spatial relation (e.g., intersect, overlap or touch) with the feature(s) selected in GIS. The output values are grouped in positive and negative values to separate aquifer sources from sinks. The summary includes: (1) Sources and Sinks Flux, (2) Mass, and (3) Concentration. Appendix III – *Geo-MODFLOW Summary Calculation Details* contains the detail descriptions of the generated summary calculations. Figure 3.18 shows the Geo-MODFLOW summary for the aquifer recharge of the selected area in ArcMap.

Geo-MODFLOW implements parallel processing technology to load and process large amounts of data, allowing the user to continue working in ArcMap while the groundwater data are processed or loaded.

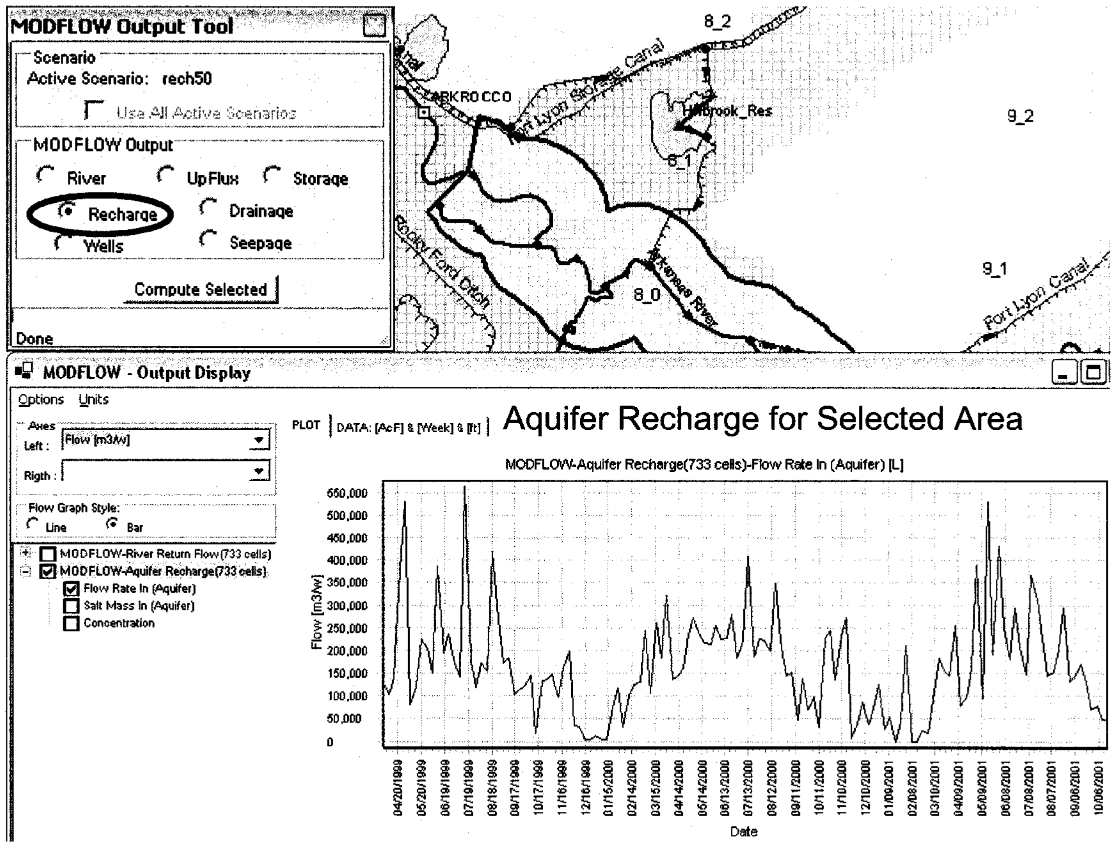

Figure 3.18 – Geo-MODFLOW summary display in ArcMap™

CUSTOMIZABLE INTERFACES AND TOOLS

Customized interfaces and tools have been implemented in the *River GeoDSS* for the Lower Arkansas River basin that illustrate the customization environments embodied in the *River GeoDSS* that accommodate the particular needs of the modeled system. The customized *River GeoDSS* uses the core underlying tools and modules but implementing custom data import and processing tools, network pre-processing and executions. Additions to the user interfaces are easily handled using .NET inheritance, with the *River GeoDSS* base-user interface inherited and enhanced for custom applications.

A custom interface is implemented for the Arkansas River basin modeling. These interface and tools are developed for evaluating and analyzing "what if" management alternatives for salinity and waterlogging remediation. The *LAR GeoDSS* provides a set of tools to import time series and water rights, and handle storage water operations and alternate points of diversion. The *LAR GeoDSS* features a Simulation Scenario Analysis Tool, which builds overall simulation-summaries of the system water quantity and quality for quick management alternative comparison. Detailed description of these custom features, and their application to the Arkansas River basin, is provided in Chapter 6.

SPATIAL OUTPUT DISPLAY

River GeoDSS enhances the standard MODSIM result display/analysis tools with a spatial visualization the modeling results in ArcMap. This tool allows simultaneous display of any MODSIM variable at all the network elements; the results can be animated to observe spatial system changes in the modeled values through the simulated period. The results are color or size coded for each of the objects in the system, so they are spatially displayed for each time step. The spatial representation of the output is a great tool for problem identification and analytical analysis of system operations and can provide information for management improvement. Figure 3.19 shows an example of the spatial result visualization in ArcMap of the Imperial Irrigation District network; where the surface inflow to demand and sink nodes is size coded, and the percent full of canal links is color coded. The *River GeoDSS* interface to control the display options and results animation is also shown in Figure 3.19; in addition, the interface displays the currently displayed time step and date.

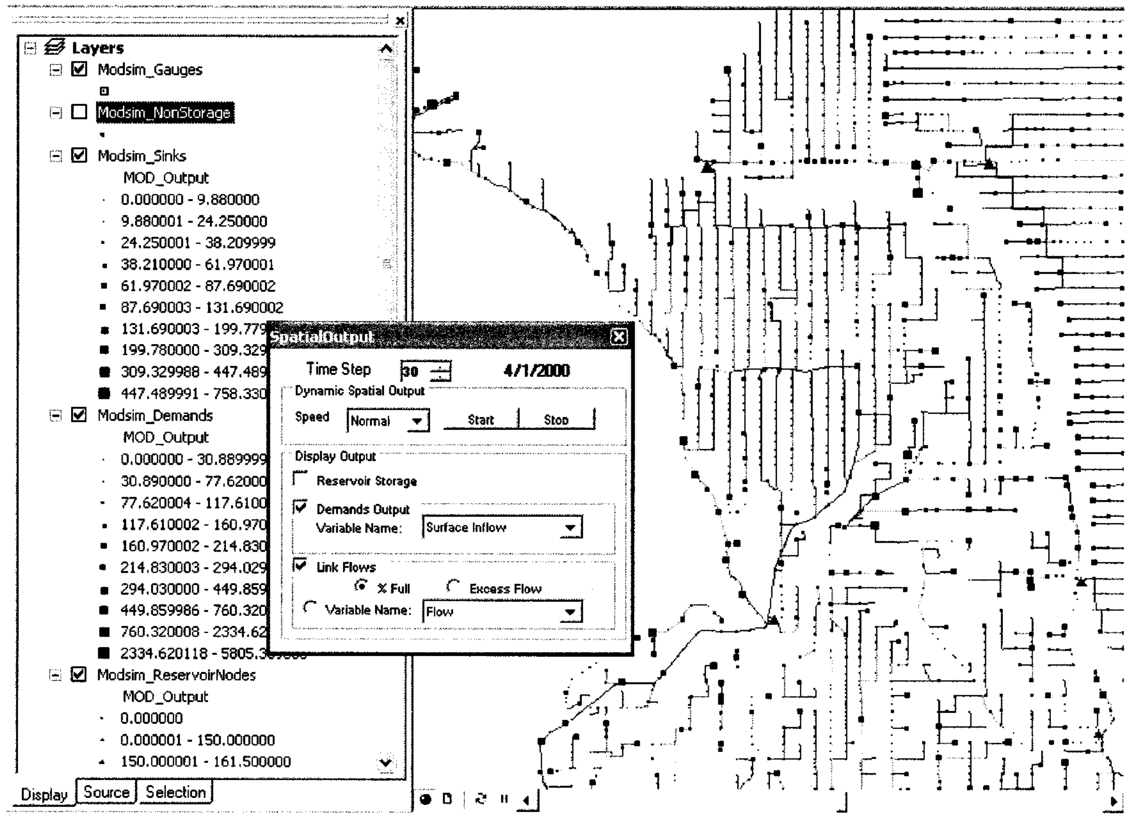

Figure 3.19 - *River GeoDSS* spatial results visualization example in ArcMap™

CHAPTER 4

ANN ASSISTED WATER RESOURCES MODELING

STREAM-AQUIFER INTERACTION MODELING

Stream-aquifer interaction is the fundamental component to address river basin conjunctive use modeling, for rivers that are hydraulically connected to a phreatic aquifer. Simplified stream-aquifer response models are generally incorporated into river basin models [e.g., Dai and Labadie 2001 and Kansas Hydrologic-Institutional Model (Burkhalter 1997)], but they fail to adequately capture the complex dynamic and spatial characteristics of the system response (Fredericks et al. 1998). An alternative methodology for modeling stream-aquifer interactions at the river basin scale is presented that integrates artificial neural networks (ANN), geographical information system (GIS) and regional-scale MODFLOW-MT3DMS groundwater modeling. The methodology is based on the development of dynamic, spatially dependent relationships between basin scale measurable system characteristics, which directly or indirectly trigger aquifer stresses, and the stream-aquifer interaction. GIS provides the framework for managing and preprocessing the extensive spatio-temporal database required for building the dataset used to explore and derive the relationships. An ANN is used to extract the relationships between the explanatory variables and the stream-aquifer interaction, with MATLAB™ (MathWorks, Inc) providing the foundation for training, validating and analyzing the ANN. A calibrated regional-scale finite difference groundwater model (MODFLOW) and the associated water quality model (MT3DMS) are used to represent stream-aquifer interaction in both historical system operations and simulated management alternatives.

The methodology is designed and implemented to be coupled with the river basin network flow model Geo-MODSIM. The coupling is rooted in the linkage of geo-referenced system features and characteristics to geo-referenced river basin network flow model objects. Complex stream-aquifer interactions are embodied in the trained ANN, which is embedded in Geo-MODSIM for providing accurate water quantity and quality conjunctive surface and groundwater modeling. The methodology presented herein is aimed to the construction of a robust and realistic river basin scale decision making support tool. The Lower Arkansas Valley in Colorado, from Pueblo Reservoir to the Colorado-Kansas State Line, is used to illustrate the method and demonstrate the potential of its application.

Regional Scale Groundwater Modeling

The Department of Civil and environmental Engineering at Colorado State University has been conducting research in the Lower Arkansas River, defined from Pueblo Reservoir to the Colorado-Kansas State Line, for many years (Gates et al. 2006). Figure 4.1 shows the location of the current (upstream) and in-progress groundwater modeled areas, where the upstream modeled area is approximately one-fourth of the Lower Arkansas River Valley.

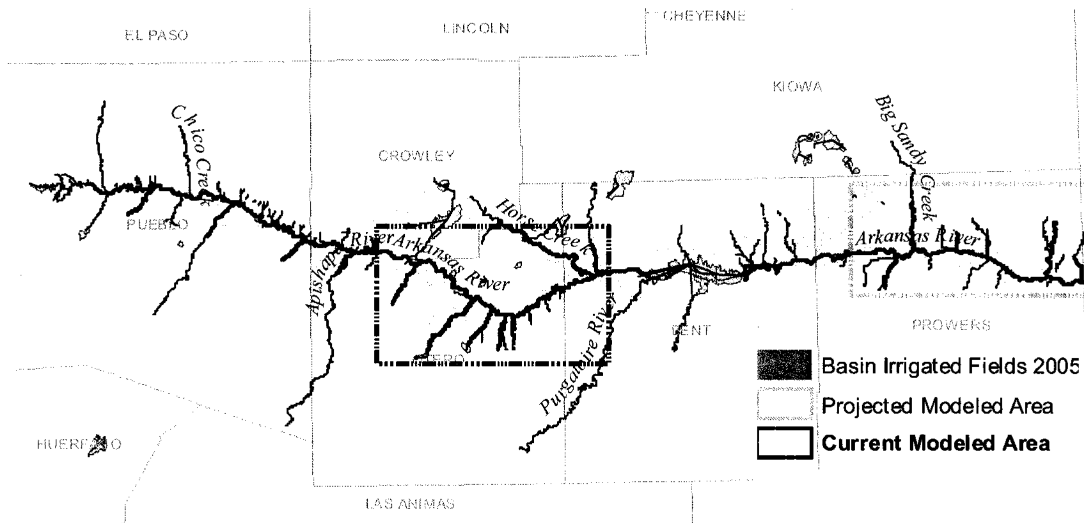

Figure 4.1– Regional-scale groundwater modeled areas

Management alternatives were engineered and modeled at the regional-scale to mitigate salinity and waterlogging problems and sustain agriculture in the area (Burkhalter 2005). Management alternatives included combinations of: aquifer recharge reduction, canal seepage reduction, groundwater pumping increase, and sub-surface drainage improvements. Burkhalter (2005) modeled the baseline and 38 alternatives including: (1) nine scenarios of aquifer recharge reduction from 10% to 90%, (2) seepage reduction levels of 50%, 70% and 90%; (3) 90% seepage reduction over 20% of the irrigation canals length, (4) canal lining scenarios of 90% seepage reduction in Holbrook, Ft. Lyon, Rocky Ford, Catlin, Otero and Highline canals, (5) drainage improvement scenarios with tile drains installed in selected fields at spacing of 50m, 75m, 100m, and 150m, (6) groundwater pumping increases of 25%, 50%, 100%, and 200%, (7) combinations of recharge reduction and seepage reduction of 30%-50%, 50%-90%, and 80-90% respectively, (8) recharge reduction and drainage improvement of 30%-100m, 50%-50m, and 80%-50m respectively, (9) combination of seepage reduction and drainage improvements of 50%-100m and 90%-

50m respectively, and (10) combination of recharge reduction, seepage reduction and drainage improvement of 30%-50%-100m, 50%-90%-50m, and 80%-90-50m. This transient model is an important resource for understanding stream-aquifer interaction and evaluating the aquifer response to salinity remediation strategies in the basin (Burkhalter and Gates 2005; Burkhalter and Gates 2006).

Approach

The methodology developed herein learns from the detailed regional groundwater modeling effort to model the stream-aquifer interaction at a larger-scale (i.e., the basin scale). The ANNs have been demonstrated as a powerful tool to describe complex relationships between sets of explanatory variables and observed data (Rogers 1992; Maskey et al. 2000; Govindaraju and Ramachandra 2000). In particular, Bowers and Shedrow (2000), Sandhu et al. (1999), and Parkin et al. (2007) have successfully applied ANNs to predict combined effects of the river-aquifer system. Detailed modeling of groundwater basins requires an extensive set of system characteristics that are pertinent to the specific modeled area. Many of these characteristics are not available at basin scale, or in adequate resolution to be reliable. Therefore, traditional groundwater modeling parameters cannot be used for the ultimate goal of basin scale modeling. However, there are events that indirectly influence stream-aquifer interaction such as precipitation, canal diversion, river flow, etc. Combining the occurrence of these events together provides are indicators of not only the temporal, but the spatial system states. A methodology is needed to define explanatory variables that adequately represent system state changes to provide guidance in predicting stream-aquifer interaction. The selected explanatory variables must be available (i.e., measurable) at basin scale. The innovative methodology proposed herein predicts stream-aquifer interactions using an ANN which is trained with current and previous basin-wide-measurable system states. The ANN is trained using (1) a detailed well-calibrated quantity and quality groundwater model representing the regional response of the aquifer (i.e., river return flows, river depletions and salt loads to the river) and (2) basin-wide quantifiable system state variables. The ANN training ("learning") process develops dynamic relationships between the inputs and outputs as embodied in the training data set that captures the complex nonlinear spatially distributed stream-aquifer response to system stresses. The relationships learned by the ANN can be used to prescribe the stream-aquifer interaction in areas where detailed groundwater modeling is not available. GIS is used in building the ANN training and testing datasets as spatially grouped by area-buffers. The ANN output variables are queried using the *River GeoDSS* Geo-MODFLOW extension.

The developed ANN can be spatially linked with the surface basin scale model (Geo-MODSIM) for efficient and practical conjunctive use modeling. In addition, embedding the ANN within river basin decision support tools eliminates the computational burden of directly incorporating realistic numerical finite difference models.

ANN Development

Spatial Variable Grouping

Aquifer responses can vary significantly, even within proximate locations or contiguous cells. When stream-aquifer interaction is analyzed over larger areas, some of the local variability is smoothed, resulting in increased predictability. Return flow volumes and concentrations are modeled in aggregated areas that extend to the adjacent alluvial irrigated valley around the main stream (i.e., the Arkansas River). These areas groupings are created from 15-km river segments in an attempt to maintain comparable predictions per unit length. The boundary of each grouping area follows, for the most part, the sub-watershed boundary created from the most downstream point of the river segment. Figure 4.2 shows the stream-aquifer interface modeling grouping areas in the Lower Arkansas Valley. The grouping areas are sequentially numbered from upstream (east of Pueblo Reservoir) to downstream (Colorado-Kansas State Line). ArcHydro tools were used to delineate the sub-watersheds to guide the grouping areas boundary definition (see Appendix III – *Stream-Aquifer Interaction Grouping Areas* for details).

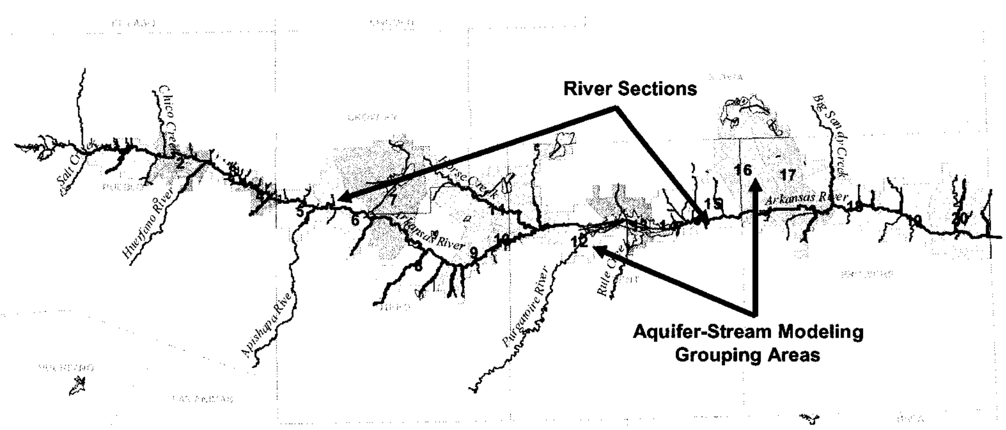

Figure 4.2 – Stream-Aquifer Modeling Grouping Areas in the Lower Arkansas River Valley

Since the aquifer responds to stresses as a function of distance from the stress, it is expected that more proximate stresses have more impact on the aquifer response. The Arkansas River is expected to be the most influential system element for the aquifer in the grouping area. Figure 4.3 shows an example of flow directions in MODFLOW groundwater modeled cells in the Arkansas Valley regional-scale model. In this example, the influence of the main stream (Arkansas River cells) on groundwater flow direction in the vicinity of the river (including areas close to the tributaries where arrows are parallel to the tributaries) is clearly evident. In contrast, for cells father from the river, the direction of the flow is toward the tributaries. The canal lines (solid light blue) seem to have less influence on the direction of the groundwater flow, although canal stage will likely have a significant impact on the magnitude of flows in/out of the aquifer.

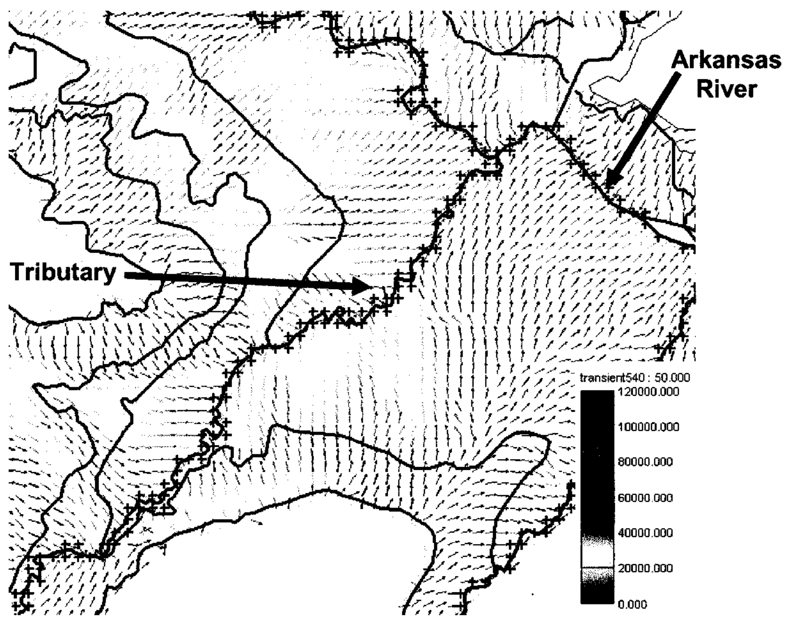

Figure 4.3 – MODFLOW Groundwater flow direction example

Surface water bodies in the system also play an important role in the groundwater flow direction. Figure 4.4 shows another example of the direction of the groundwater model cells, where it is evident that surface water interaction with the aquifer influences the groundwater flow direction.

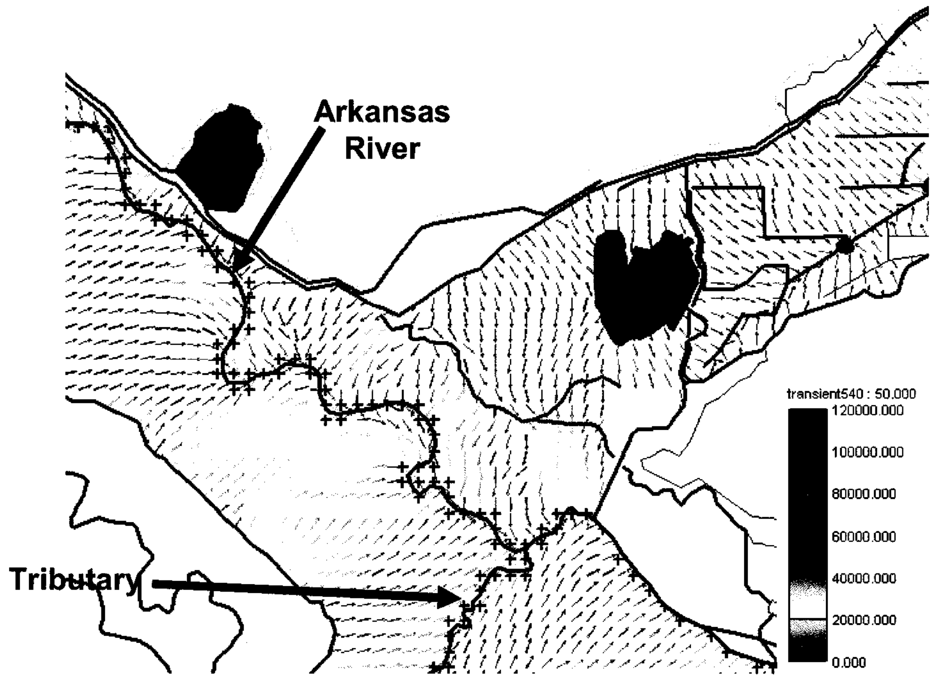

Figure 4.4 – Groundwater flow direction example

From the previous analysis, it can be inferred that stresses located in close vicinity to the main stream will have the most significant effects on stream-aquifer interaction. In the case of tributary stream-aquifer interface modeling, stresses farther away from the main stream will play a more important role than in the main stream-aquifer interaction modeling. The spatial relevance of system state changes is incorporated by grouping variables according to the locations where they occur. For this purpose, area-buffers surrounding the stream are created using incremental buffer zones along the main stream segment. The first area-buffer extends 3 km east and west of the stream, while the second area-buffer extends 6 km east and west of the first area-buffer external boundary. Figure 4.5 illustrate the area-buffers for the grouping areas in the groundwater modeled region. The stream-aquifer interface for the main river is located in the first buffer, whereas tributary stream-aquifer interactions can occur in any of the area-buffers.

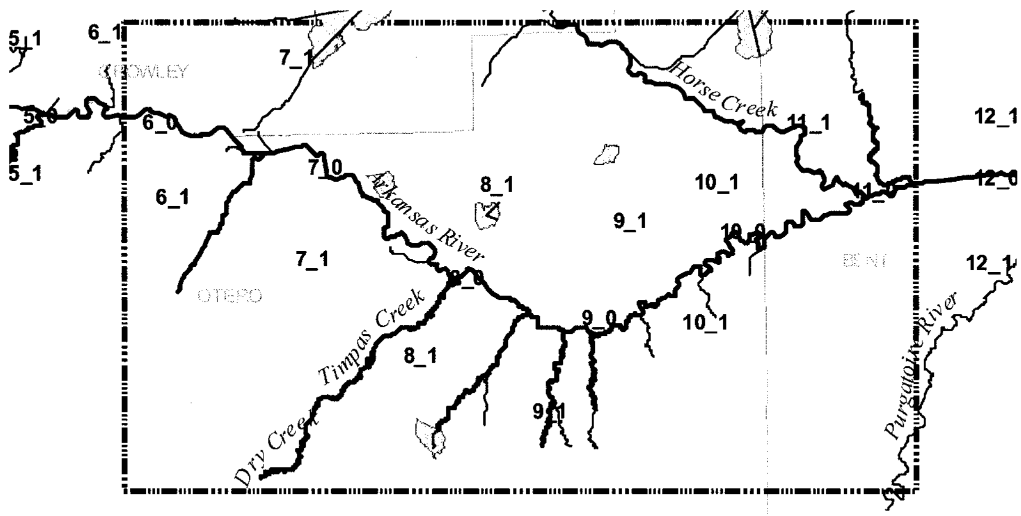

Figure 4.5 – Buffer-Areas for variable aggregation inside the stream-aquifer modeling grouping areas

Explanatory Variables

The explanatory variables are designed to capture the system state and provide the ANN with pertinent information about the current state and magnitude of change with respect to previous states in order to predict aquifer return flows and salt loadings to the surface water system.

Explanatory variables are aggregated by grouping areas and depending on the nature of the explanatory variable further sub-divided by area-buffer. Explanatory variables aggregated per grouping area include (1) average main stream elevation from sea level, (2) stream length in the grouping area, (3) tributary stream lengths in the grouping area, and (4) the average system stream flow in the grouping area. The explanatory variables summarized per area-buffer in the grouping areas include (1) average terrain elevation with respect to the main stream elevation, (2) lengths of the canals, (3) canal average elevations with respect to the average main stream elevation, (4) areas of water bodies in the area buffer, (5) average elevation of the water bodies with respect to the main stream elevation, (6) extent of irrigated fields, (7) average diversion per irrigated area for fields in the area-buffer, (8) the number of active pumping wells, (9) total groundwater pumped volume, (10) total precipitation over the area-buffer, (11) average canal seepage in the area-buffer, and (12) average aquifer recharge in the area-buffer, as computed for a canal irrigating land in the area-buffer as a fraction of water available to the area-buffer fields. Intensity indicator variables for potential changes in the modeling of various management scenarios are included as explanatory variables. Variables indicating percentage of increase pumping from the baseline and drainage intensity are computed for each grouping-area. Variables reflecting seepage reduction from the baseline and percentage of recharge reduced from the baseline are calculated for each area-buffer as a function of the corresponding overlying canals and irrigated fields in the area-buffers. Appendix I describes the explanatory variables in detail including *River GeoDSS* database keywords and processing methods.

Training in Passes

As discussed previously, explanatory variables that are dependent on Geo-MODSIM simulations can create instability in the predictions if the training values significantly differ from the simulation values. The aforementioned training technique attempts to alleviate this effect. All the scenarios to be included in the training are executed in Geo-MODSIM prior the first training as an initial approximation in order to mimic all important model conditions, such as scenario demands, seepage, and reservoir storage. In the baseline network calibration, the *River GeoDSS* provides gains and losses to closely match the measured flows that bring flows in the system closer to a conjunctive use simulation flow. The ANN training dataset is then generated using the initial set of Geo-MODSIM results. Using the trained ANN, a new execution of the Geo-MODSIM networks is performed that allocates water according to the new system conditions, including the ANN predicted stream-aquifer interaction. The explanatory variables for the ANN are computed based on the first MODSIM run in order to lessen the impact on the predictions. A second ANN training session can then take place using the most recent MODSIM results to build the new training dataset. Figure 4.6 shows the sequence used to train the ANN in several passes or sequences.

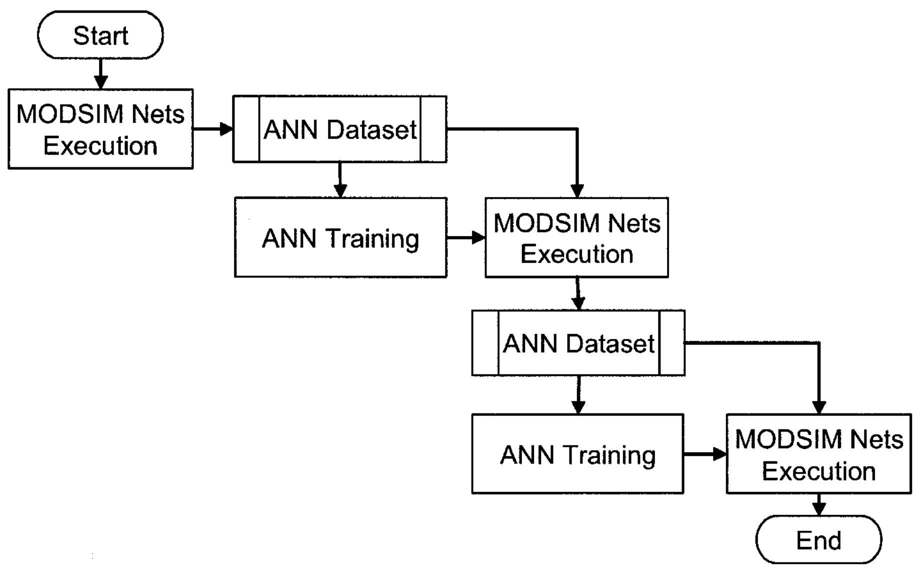

Figure 4.6 – ANN training in passes diagram

Using this iterative process between the ANN training and *River GeoDSS* simulation, it is possible to refine the explanatory variable dataset to more accurately capture the complexity of the system model. In the future, this method can provide a valuable contribution to refine the groundwater model by providing a better representation of spatial and temporal water availability, especially for scenarios where no historical measurements are available.

Training Dataset

The ANN training dataset is created using a set of tools that (1) extract the spatially dependent variables from the GIS spatial database, (2) query baseline and management alternative Geo-MODSIM results for the modeling dependent variables, and (3) summarize temporal-varied variables from the time series database per modeling time step.

Geo-Processing Tools

A set of tools have been implemented in VB.NET using ESRI-ArcObjects to geo-process and extract explanatory variables aggregated by grouping area or area-buffers. These tools are packed under a user interface (Figure 4.7), which is accessed from the *River GeoDSS* toolbar using the button  .

The data management interface allows system elements to be associated with the name of representing feature class (from the available in the ArcMap™ project). The system elements defined in the data management tool include irrigated fields, pumping wells, canals lines, the Digital Elevation Model (DEM), water bodies, the main stream and the grouping areas. In addition, the data management interface allows selection of file paths and file names for the time series database, the precipitation database, water quality database, and the ANN buffers and training datasets.

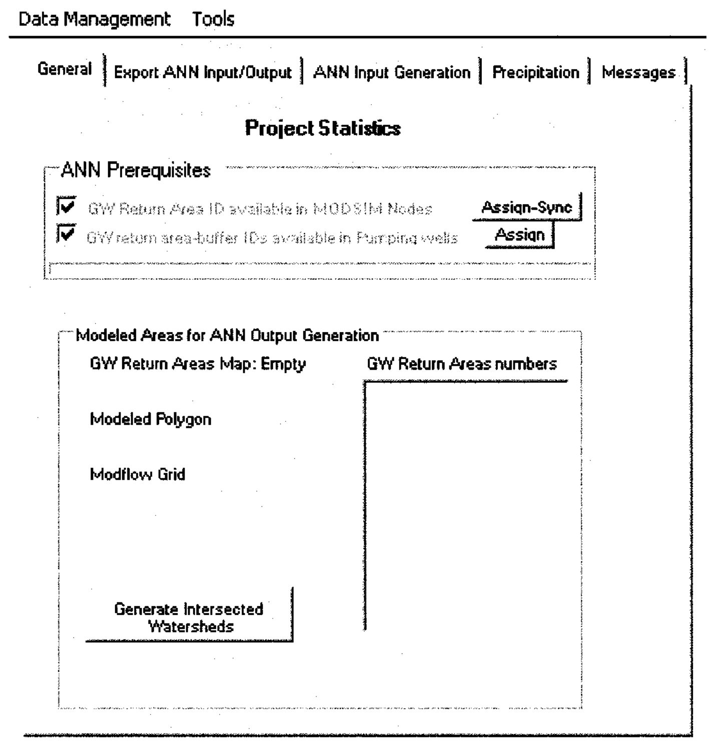

Figure 4.7 – Geo-tool user interface for ANN training dataset processing in ArcMap™

Spatial Precipitation Tool

The *precipitation* tab (Figure 4.7) gives access to a tool for generating a database with tabular precipitation summarized per area-buffer and per time step. This tool summarizes precipitation based on a set of precipitation raster maps, which are the result of processed NEXRAD data or raster maps generated from point-measured precipitation, using a *River GeoDSS* tool () to generate raster maps from National Weather Service (NWS) and Colorado Agricultural Meteorological network (CoAgMet) stations (Figure 4.8). The raster maps folder location is specified in the data management interface. The generated raster files are named with user defined prefix (data management interface) and the simulation time step start date.

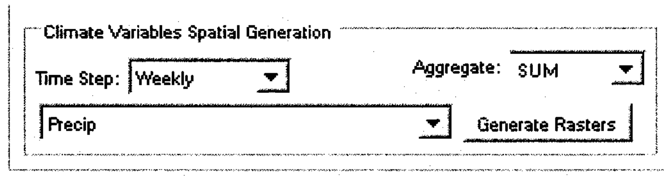

Figure 4.8 – *River GeoDSS* climate raster maps from point-based data generation interface

ANN Input Generation Tool

The *ANN Input Generation* tool processes the available spatio-temporal data and stores the summaries in a database referred as the *buffers database* (assigned in the Data Management interface). The user specifies the number of area-buffers and the base size of the buffer, i.e., the first buffer (Figure 4.9). These parameters are used in the grouping area polygons to create the area-buffers and generate a set of support summary tables and processed GIS feature classes for the creation of the ANN training dataset.

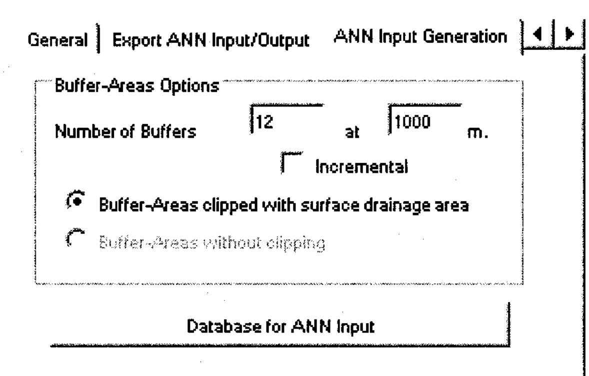

Figure 4.9 – ANN training dataset preprocessing interface

MODSIM Inputs Tool

This tool uses MODSIM output files to extract the model related explanatory variables. This tool allows using in the ANN training dataset results of complex *River GeoDSS* modeling, including water rights allocation, calibration flows, temporal and spatial water availability and accurate modeling of scenarios dependent variables such as local inflows (vertical drainage scenario), diversions, seepage and even predicted return flows.

Geo-MODFLOW in ANN Training

Geo-MODFLOW tools are used to build the ANN training dataset. The geo-referenced grid cells are geo-processed (clipped) to provide the groups of cells included in the analysis of each of the grouping areas. The geo-processing results include cells per area-buffer (*BGridCells* feature class) and MODFLOW river cells classified by grouping area for both the main stream and the tributaries (*BRiverCells_XX* feature class). These processed feature classes are stored in the *buffers* database. The variables included in the training dataset are: (1) total volume returned to the main stream and tributaries, (2) total salt returned to the main stream and the tributaries, (3) calculated concentration of the return flows, (4) grouping area aquifer recharge, (5) grouping area pumping and corresponding salt load, (6) simulated drained volume and corresponding salt load, and (7) the area-buffer based canal seepage. Details on these MODFLOW modeled variables are provided in Appendix I – *MODFLOW-MT3DMS Variables for ANN Training.*

Export ANN Input\Output Tool

The *Export ANN Input/Output* tool uses the *buffers* database support tables and GIS processed feature classes to generate datasets with inputs and outputs for all simulation time steps and all modeled management alternatives. The user specifies the type of data to be included in the dataset (i.e., input or output data) and the type of output (i.e., quantity or quality), as well as the type of grouping areas to include. Although explanatory variables for simulation grouping areas can be generated, some may lack modeled output variables. Figure 4.10 shows the user interface for the ANN training dataset generation. The *River*

GeoDSS Simulation Scenario Manager is used to display/enter preferences for the scenarios to be used for training, including the MODFLOW file locations and characteristics of alternatives for pumping increase, recharge reduction, seepage reduction and drainage density. The tool generates an MS-Access database containing the ANN training dataset; details on the generated database structure are found Appendix I – *ANN Training Database*.

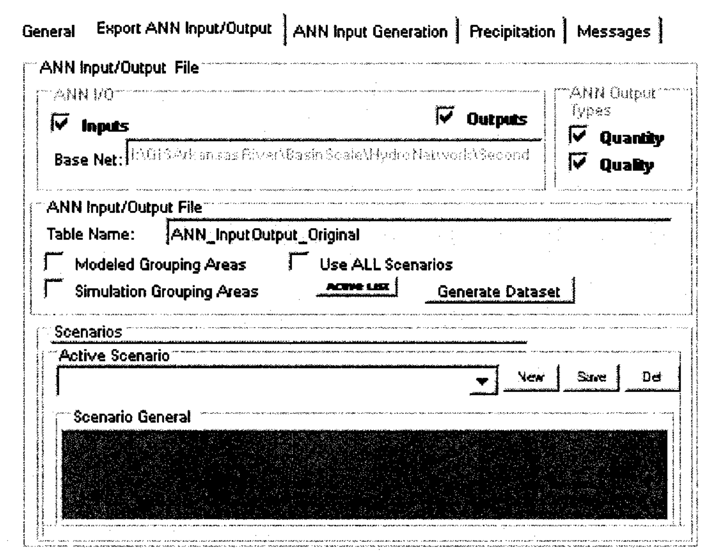

Figure 4.10 – ANN training dataset generation user interface

ANN Database Management Utility

This tool filters and processes the dataset generated by the geo-processing tools to create files for ANN MATLAB training and *River GeoDSS* simulation.

The *ANN Database Management* utility adds four variables to the dataset, making them available for the ANN training. The variables introduced are: (1) *NETRetFlow_CalcArk* and *NETRetFlow_CalcTrib* that use the MODFLOW output variables to compute the net volume from the aquifer to the river and to the tributaries, respectively, where a negative sign indicates water leaving the aquifer, (2) *RechReduction*, which uses the user defined baseline to compute reduction in recharge to the grouping areas, and (3) *SeepReduction_* that computes, per area-buffer, the seepage reduction from the user-defined baseline scenario.

This tool implements two MS-Access user interfaces. The first one (Figure 4.11) allows data grouping, filtering the initial time steps (i.e., excluding them from training) and applying factors to the dataset variables to facilitate the training. In addition, this user interface allows splitting the dataset into groups based on the month number for separated ANN training under different seasonal conditions (e.g., irrigation and non-irrigation). Experimentation on the ANN stream-aquifer interaction modeling showed insignificant improvement when training the ANN for irrigating and non-irrigating seasons; therefore, a single period was selected for this study and this ANN split option is not available in the *River GeoDSS*.

The second interface (Figure 4.12) allows selection of the training dataset generation parameters, including (1) the grouping areas for training and testing, (2) explanatory variables, (3) output variables to be predicted by the ANN, (4) previous time step variables and number of previous time steps to be included in each explanatory variable set; (5) dataset generation options, and (6) naming conventions for the output files. Explanatory variables with "_" indicate that they will be included for all the area-buffers specified in the preferences. This interface processing engine implements an algorithm that includes input/output variables from previous time steps to simulate a recurrent effect that allows the neural net to capture time-varying patterns. Although, the feedback is static, and it will not change during training based on the actual outputs, as it would in a Jordan network (Jordan 1990). The advantage of having the outputs included in the inputs is that the training dataset can be randomly extracted from the entire dataset. This utility exports a group of text files for MATLAB ANN training and *River GeoDSS* simulation support; the files names and description are available in Appendix I – *ANN Training Dataset Files Description.*

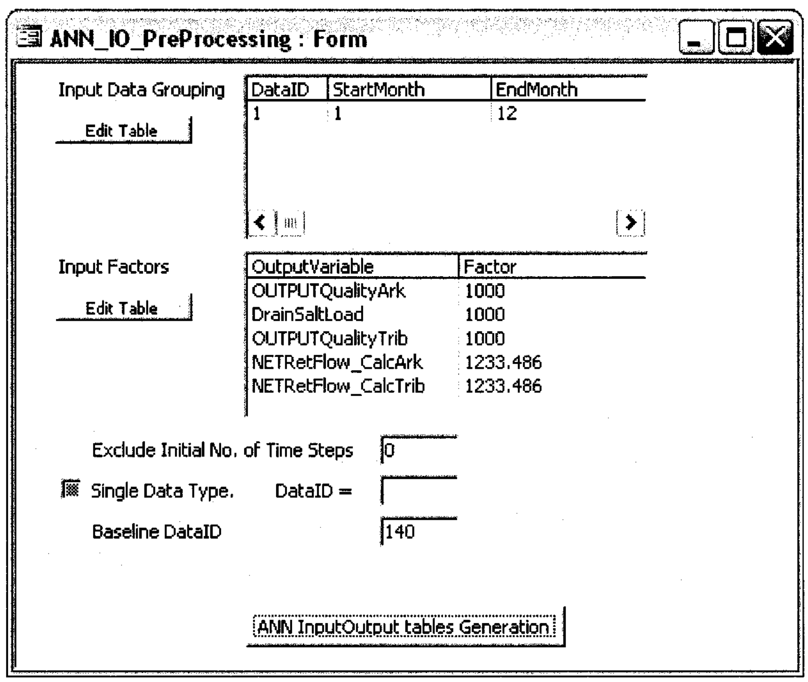

Figure 4.11 – ANN training dataset pre-processing interface

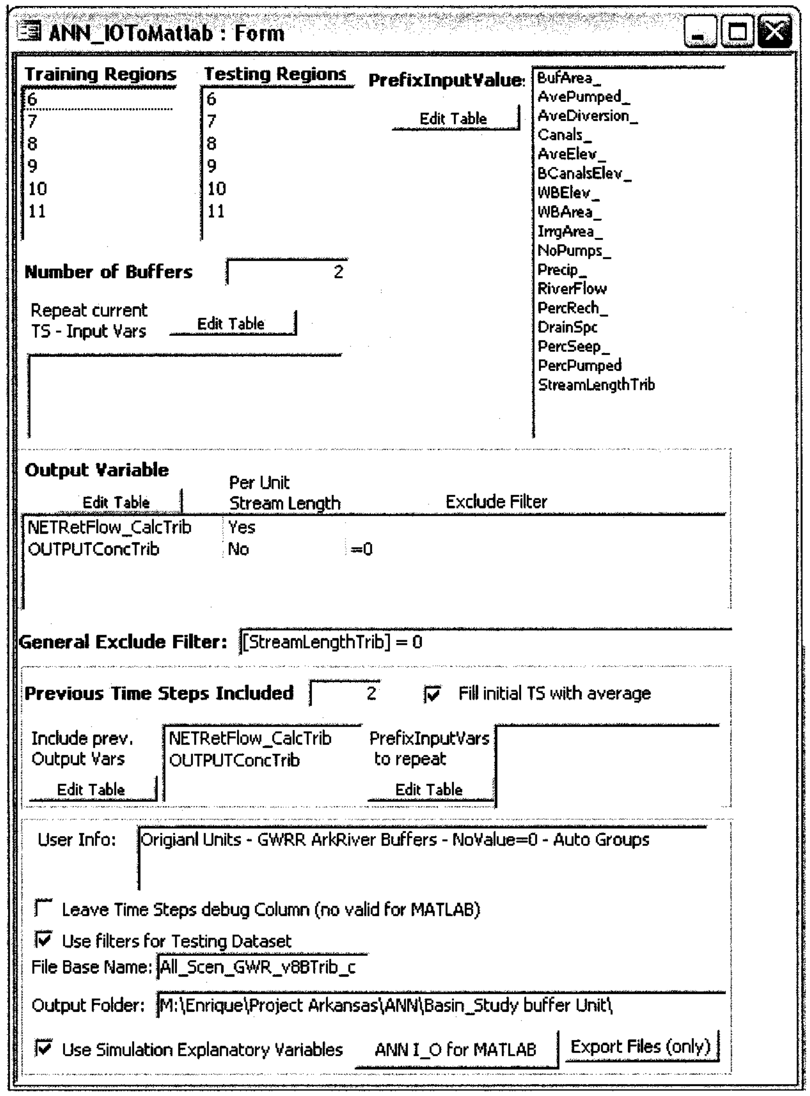

Figure 4.12 – ANN training dataset preferences interface

MODSIM Reservoir Operation in the Arkansas River System

Explanatory variables such as the flow and diversion (from the Geo-MODSIM modeling) play an important role in the set of explanatory variables. In addition, the reservoir operation rules are important for water allocation and, consequently, in the Geo-MODSIM flow calculation. Two reservoir operating rules were implemented to generate the ANN training datasets. The first one sets the targets to historical levels for Pueblo and John

Martin Reservoirs. The second operating rule uses reservoir layers with incremental costs to balance storage water between the two reservoirs. Using historical reservoir levels as targets prevents storage of water above the historical levels, but will satisfy historical water rights and river compact requirements by releasing storage water if needed and replenishing it as soon as possible. The reservoir layer balancing approach uses incremental costs in the user-defined reservoir layers to dictate the allocation of water in the reservoir system. Calibration of layer balancing operating rules includes setting the reservoir layer costs to match as close as possible the historical levels in the reservoir, so that system flows in the baseline network with layer balancing operating rules are close to the baseline flows with the first operating rule. Difference in MODSIM simulations are noticeable in the scenario simulations where "free" water can be stored in the reservoirs rather than released down the system.

The sets of baseline and scenario MODSIM runs for each operating rule are used to generate two separate ANN training datasets. The dataset generated with the set of MODSIM runs using the historical level as reservoir targets is referred to herein as *Dataset_A* and the dataset generated with reservoir layer balancing is referred to as *Dataset_B*.

ANN Training

Basin-scale stream-aquifer interaction modeling is achieved with two independent ANNs. The ANN training characteristics and relevant explanatory variables for stream-aquifer interaction modeling of the Arkansas River versus its tributaries are significantly different. Therefore, an ANN for each type of training is implemented to accurately model the system water conjunctive use. This separated training process gives the ability to better filter the dataset, thereby improving performance by training and predicting over more homogeneous input\output cases. For both the Arkansas River ANN and the tributaries ANN the explanatory variables are spatially group using area-buffers in Figure 4.5.

Grouping areas (6 and 11) located near the edges of the groundwater modeled area require special handling since if only the modeled area is considered, it results in explanatory variables values of smaller magnitude due to the smaller number of features considered, rather than if the entire area were taken into account. Predictions per unit length in grouping areas 6 and 11 are assumed to remain similar to the modeled values per unit length, which includes only a portion of these grouping areas. Therefore, the ANN training dataset is built assuming that explanatory variables for the entire grouping areas 6 and 11 (including no modeled areas) will produce the same results per unit length of stream as the values calculated in each modeled area. Using this approach all the grouping areas for training will have a common ground for comparison in terms of their river lengths and area-buffer extents.

Both *Dataset_A* and *Dataset_B* are used to train ANNs for the basin-scale stream-aquifer interaction modeling. Each of the datasets produces ANNs that attempt to predict the same phenomena, thereby giving an indication of the sensitivity of the predictions to changes in the MODSIM-reliant explanatory variables.

The training dataset for the ANN that models the stream-aquifer interaction is prepared using the preferences displayed in Figure 4.11 for the ANN Database Management Utility, including (1) all months in a single group, (2) a factor of 1000 applied to the ANN predicted salt load related variables [i.e., salt loads to the Arkansas River

(*OUTPUTQualityArk*), salt loads to the tributaries (*OUTPUTQualityTrib*), and salt loads in drained water(*DrainSaltLoad*)] to reduce their magnitude on the ANN training, and (3) a factor of 1233.486 to convert the computed net return flows (*NETRetFlow_Calc*) from m^3 to acre-ft.

Custom MATLAB Training Tools

A set of customized tools were developed using the MATLAB® neural network Toolbox libraries. These tools allow importing the training datasets, selecting training parameters, preparing the data, training and testing the ANNs. The training process begins by browsing for the ANN Database Management utility exported files. A set of dialogs allows the user to select options for the ANN training. The user-selected options include scaling type, training/testing/validation groups to be generated, the size of the training dataset, the type of network, the network structure, and the training parameters.

The Training Tool uses the training dataset created by the Database Management Tool (the testing dataset is used later for simulation performance analysis). This training dataset is divided in training, testing and validation groups according to the user preferences. The testing/validation groups are used for the backpropagation ANNs to avoid overtraining. These groups consist of training cases that are not presented to the ANN for training but rather used for stopping the process when overtraining is detected. If later in the training process the user selects a type of network that does not require the testing and validation groups, these cases are merged back with the training cases.

ANN Explanatory Variables Automatic Scaling

The pre-processing algorithm automatically selects between two scaling methods: (1) Min/Max scaling (*MnMx*) and (2) Standard Deviation (*Std*) scaling.

In *MnMx* scaling, the explanatory variables are scaled between -1 and 1 using the following transformation equation:

$$pn_i = 2 * \frac{(p_i - min_p)}{(max_p - min_p)} - 1$$

where min_p = the minimum of explanatory variable p and max_p = the maximum value for the explanatory variable p.

The *Std* scaling transforms the data so that its mean is 0 and a standard deviation of 1 using the following equation to transform the variables:

$$pn_i = \frac{(p_i - mean_p)}{std_p}$$

where pn_i = the transformed value; p_i = the explanatory variable value; $mean_p$ = the mean of the explanatory variable p and std_p = the standard deviation of the explanatory variable p.

The *MnMx* scaling option is used for explanatory variables when the mean value of the *MnMx* transformed data falls between 0.25 and -0.25; otherwise, *Std* scaling is used. This rule attempts to maintain a symmetrical spread of the scaled data around the 0 value. In an attempt to reduce the effect of errors in the previous time step explanatory variables during simulation, a tighter interval of -0.1 and 0.1 is used for assigning *MnMx* scaling to these variables, resulting in a *Std* scaling in almost all cases. The output variables are always scaled using the *MnMx* method.

ANN Training Dataset Size

The combination of about 130 weekly time steps for the baseline and 36 scenarios produces a very large dataset for training. Training an ANN with large dataset becomes impractical or impossible due to computing limitations. Therefore, the custom ANN training tool allows the user to randomly select a specified number of cases for training (Figure 4.13). The remaining training cases are added to the performance testing dataset.

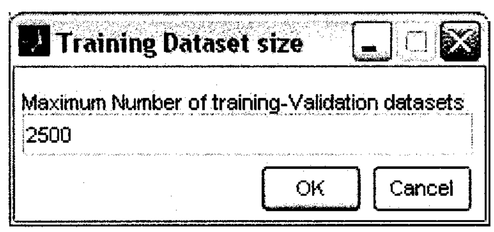

Figure 4.13 – MATLAB ANN training tool dataset size user-dialog

Neural Nets Types and Training Preferences

Four types of neural nets are implemented in the MATLAB training tool: (1) feed-forward backpropagation, (2) Elman backpropagation neural network, (3) Generalized Regression Neural Net (GRNN) and (4) Radial Basis Neural Net (RBNN).

Backpropagation type networks use a training method that relies on sequential improvement of weights and biases to minimize errors between the predicted and observed values; therefore, the minimization result is a function of the initial parameters condition. A backpropagation training event is difficult to reproduce, since the initial training parameters are randomly selected, and the training might require many trials to acquire the

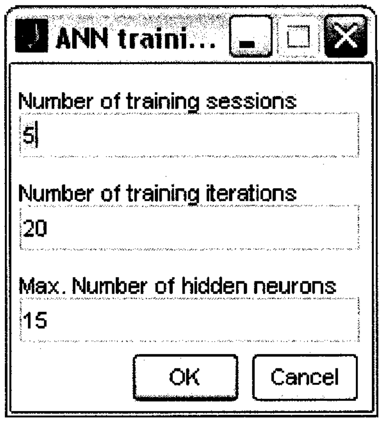

Figure 4.14 – Backpropagation Neural Net Training Dialog

desired performance. The developed training tool implements a sequential training process in which many training events in several sessions are carried out, with the best performance training selected per session. Figure 4.14 shows the user preferences interface for the backpropagation sequential tool. For each training event, the algorithm selects a random number of neurons (up to the user specified maximum); in addition, it changes the MATLAB training method (i.e., traincgf, traincgb, trainscg, traingdx, trainbfg and trainlm), and randomly selects the layers transfer function type (i.e., purelin, tansig and logsig). A weighted performance function is used to select the best trained network per session. The performance function includes training and validation mean squared errors (MSE), which are combined using a factor of 0.3 and 0.7, respectively. The performance function (f_p) is computed as:

$$f_p = 0.3 \cdot MSE_T + 0.7 \cdot MSE_V \tag{4.1}$$

where MSE_T = training dataset mean squared error and MSE_V = validation dataset mean squared error. The training process stores the best networks for all the training sessions, which are available for comparison and analysis in the custom MATLAB post-processing tools. In the feed-forward network training, additional options are available to the user such as: training stopping methods and types of network structure. The training tool implements three MATLAB training stopping methods: Early stopping, Regularization and Bayesian regularization. The user can select from two types of feed-forward neural network architectures: Feed forward or Cascade forward.

The Elman Network training follows the backpropagation training procedures described above, but is significantly more difficult and time consuming than the other backpropagation networks. Therefore, training is restricted to smaller number of sessions.

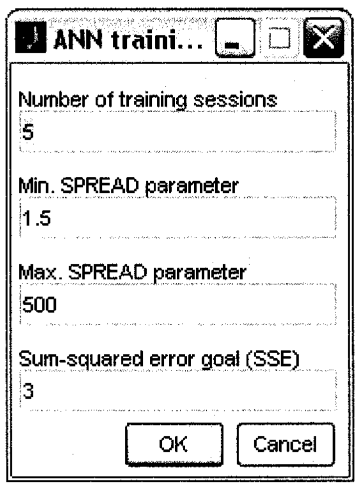

Figure 4.15 – Radial Basis NN training preferences

The RBNN type networks are trained based on the user-specified sum-squared error (SSE) goal and network *spread.* Figure 4.15 shows the user interface for the radial basis ANN training. The custom training tool trains the user-defined number of networks between the maximum and minimum *spread* until the SSE goal is reached or more than 400 neurons are required in the training event, size found to be impractical for training and prediction generalization. The training sessions are then stored for further visualization and analysis. Use of various network *spreads* results in different separations of the neurons and consequently requires different numbers of neurons to achieve the error goal. Parsimony in the number of neurons required results in better generalization capabilities of the ANN.

The Generalized Regression neural network (GRNN) is a type of radial basis network, but is rather insensitive to the *spread* parameter, as with the RBNN. Since the range of spreads with good performance is small (1 to 4), the training process becomes almost unique for each set of training datasets. In this training process, the user is only asked for the *spread* value. Commonly, the GRNN architecture results in a network with larger numbers of neurons than the regular radial basis network.

Neural Network Selection

Neural Network selection involves training different types of implemented ANNs using several configurations and sizes of datasets in order to observe and compare their performance in training/verification, overall performance (using the testing dataset) and network structure complexity. The best ANNs are compared in detail by comparing predictions for the baseline scenario at individual grouping areas. Finally, selective screening is performed to observe return flow and concentration predictions for scenarios compared with the baseline predictions. These prediction differences are essential for analysis of the management alternatives using the ANN conjunctive use modeling.

The feed-forward ANN training is disadvantageous because of the large number of training events needed to achieve good performance. Prediction performances are highly variable depending on the training event, which results in a wide range of prediction errors for the best networks. Even though one-third of the available cases (8000+) are used for training, prediction performance on the testing/validation dataset was extremely poor, in most of the cases. Based on the limited number of training events performed, the feed-forward NN seem to lack the ability to predict this complex phenomenon.

The Elman recurrent network was not used for this modeling because the nature of the training dataset is unsuitable for this type of ANN. The training cases were derived from small sets (i.e., grouping areas and scenarios) of chronological events, but these sets are not all sequential. Since, the network training relies on the order in which the explanatory variables are presented, combining cases from different sets results in misinterpretation of the training dataset.

The GRNN prediction is limited by the size of the training dataset, with the maximum number of training cases found to be less than 500 due to computer memory limitations. The GRNN training produced ANNs with the number of hidden neurons equal to the number of training datasets, which indicates that only the randomly selected cases will influence the prediction. The GRNN training is repeatable and rapidly processed, with acceptable overall performance but poor generalization. The ANN testing results show smooth predictions but including large prediction errors in some cases. The differences between the baseline and scenario predictions were inconsistent with the modeled differences.

This experimentation with different ANN architectures and configurations pointed to selection of the radial basis neural network as best suited for the modeling based on prediction performance and generalization capabilities. Upon adequate combination of parameters and error goals, the RBNN was able to model the process with a small number of neurons, and produce predictions with the smallest errors. Although for some of the test cases the correlation between the predicted and the modeled values was low, the average predictions seemed to have a relatively small error based on visual inspection of the graphical results. In addition, differences between the baseline and the management scenario predictions produced the correct prediction change direction in most cases. In many instances, the predicted differences have a similar magnitude to the differences between the modeled baseline and the corresponding management scenarios.

<u>Arkansas River Stream-Aquifer Interaction ANN</u>

For these ANNs, explanatory variables are gathered from only the first area-buffer (i.e., closer to the Arkansas River). Figure 4.16 shows the preferences used to generate the ANN training dataset that predicts Arkansas River stream-aquifer interactions using *Dataset_A*. Values from four previous time steps are used in the dataset to provide the ANN with time-varying "memory" effects. The variables made recurrent are: (1) grouping area average flows, (2) net return flows to the Arkansas River and (3) return flow concentrations. Notice that the return flow output is normalized per length of the main stream in the grouping area. Figure 4.17 shows the preferences used to generate the ANN training dataset for modeling the interaction between the aquifer and the Arkansas River using *Dataset_B*. In this case, since only data from two previous time steps are used in the dataset, the increase in the previous time steps included in the network "memory" can potentially magnify the error propagation during simulation.

The networks used to model stream-aquifer interactions in the Arkansas River basin are trained using a random set of 2500 cases. The radial basis ANN is trained for *spreads* between 2 and 150 and a SSE error goal of 15. The best performance (Equation 4.1) was achieved in both trainings using a *spread*[1]=39. The ANN internal configuration is defined in the training process based on the training parameters (i.e., *spread* and error goal). The training results in an internal configuration of 11 hidden neurons for the ANN from *Dataset_A* (*AllScen_GWR_v8BArk_b*) and 34 hidden neurons for the ANN from the *Dataset_B* (*AllScen_GWR_v8Ark*).

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[1] Best *spread* from a discrete search using the user-specified maximum, minimum *spread* and the number of training events.

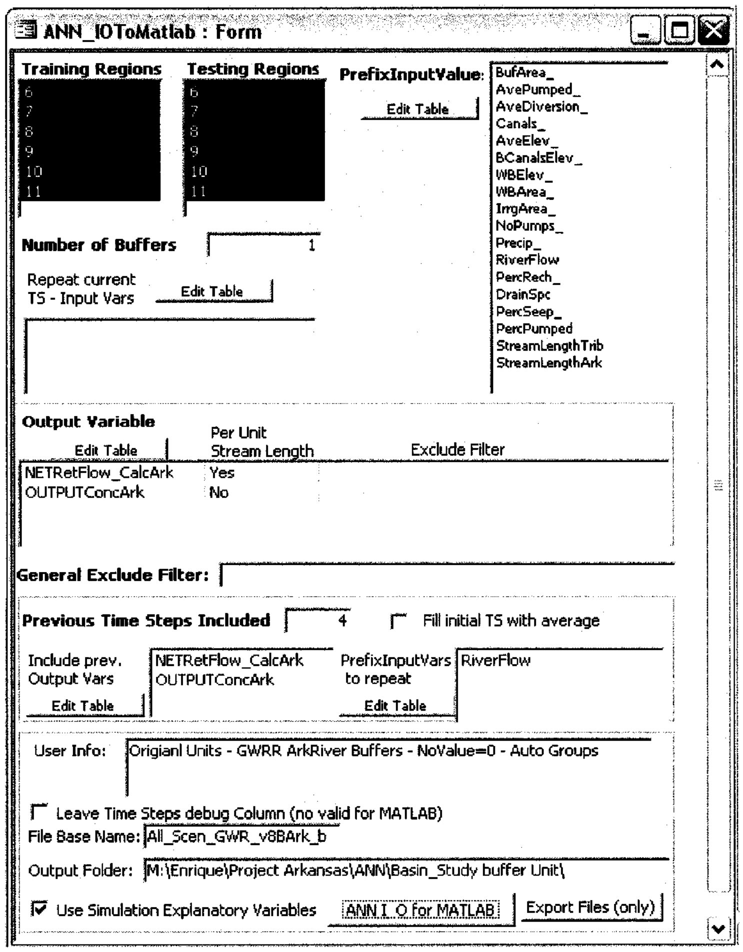


Figure 4.16 – ANN training dataset preferences for the Arkansas River stream-aquifer interaction modeling (Dataset_A)

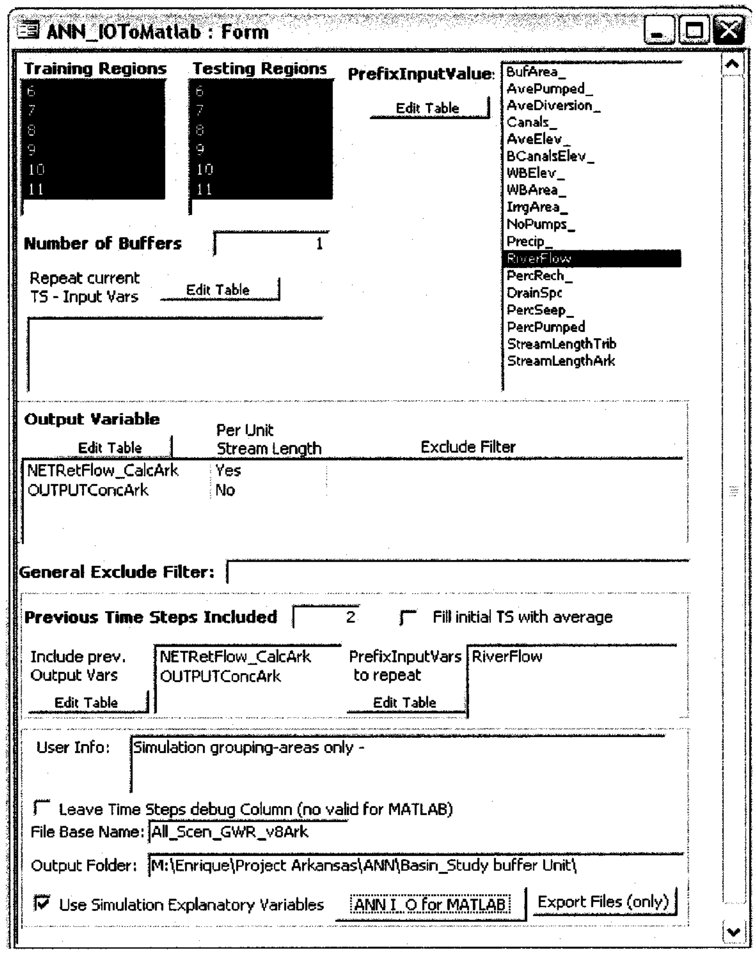


Figure 4.17 – ANN training dataset preferences for Aransas River stream- aquifer interaction modeling (Dataset_B)

AllScen_GWR_v8BArk_b Validation for Arkansas River Stream-Aquifer Interaction

The training performance analysis report (Figure 4.18) is used to visualize the main elements and statistics of an ANN training event. This report belongs to a set of reports generated by the custom ANN training tool. The performance analysis report includes plot of predictions vs. modeled values in both the training and original scales and predictions statistics in both training and testing\validation. Figure 4.18 shows the ANN training and testing prediction performance of the *AllScen_GWR_v8BArk_b* neural net to prescribe the return flow per unit length to the Arkansas River. The analysis shows the prediction performance in both the randomly selected 2500 training cases and the remaining 25000+ cases (testing\validation cases). The testing forecast bias $m(e)$= -0.002 acre-ft/km, indicating that the prediction mean is close to the mean modeled values. The testing root mean squared error per week $s(e)$ = 7.2 acre-ft/km, which provides an indication of the variability of the forecast errors. The noise-to-signal ratio $s(e)/s(y)$=0.002 indicates good accuracy since a small amount of information hidden by the noise (i.e., $s(e)$ much smaller than the modeled data variance $s(y)$). In addition, the coefficients of correlation R=0.96 and determination R^2=0.92 during training and testing, indicate a good forecast and do not show signs of overtraining.

Figure 4.19 shows the training and validation analysis for the Arkansas River return flow concentrations as predicted by the *All_Scen_GWR_v8BArk_b* ANN. The prediction statistics indicate an unbiased and accurate prediction with a high coefficient of determination of 0.99 and low noise-to-signal of 0.0001. The root mean squared error $s(e)$=48.5 mg/L.

AllScen_GWR_v8Ark Validation for Arkansas River Stream-Aquifer Interaction

Figure 4.20 shows the *AllScen_GWR_v8Ark* return flow prediction performance analysis, and Figure 4.21 displays the *AllScen_GWR_v8Ark* return flow concentration validation analysis. The prediction performances of the *AllScen_GWR_v8Ark* ANN is similar in all aspects to the *AllScen_GWR_v8BArk_b* ANN. The return flow root mean squared error $s(e)$=7.80 acre-ft/km and the return flow concentration $s(e)$=50.9 mg/L The major difference is a more complex internal structure in the *AllScen_GWR_v8Ark* network. It is believed that the main contributor to increases in complexity is usage of fewer previous time steps explanatory variables.

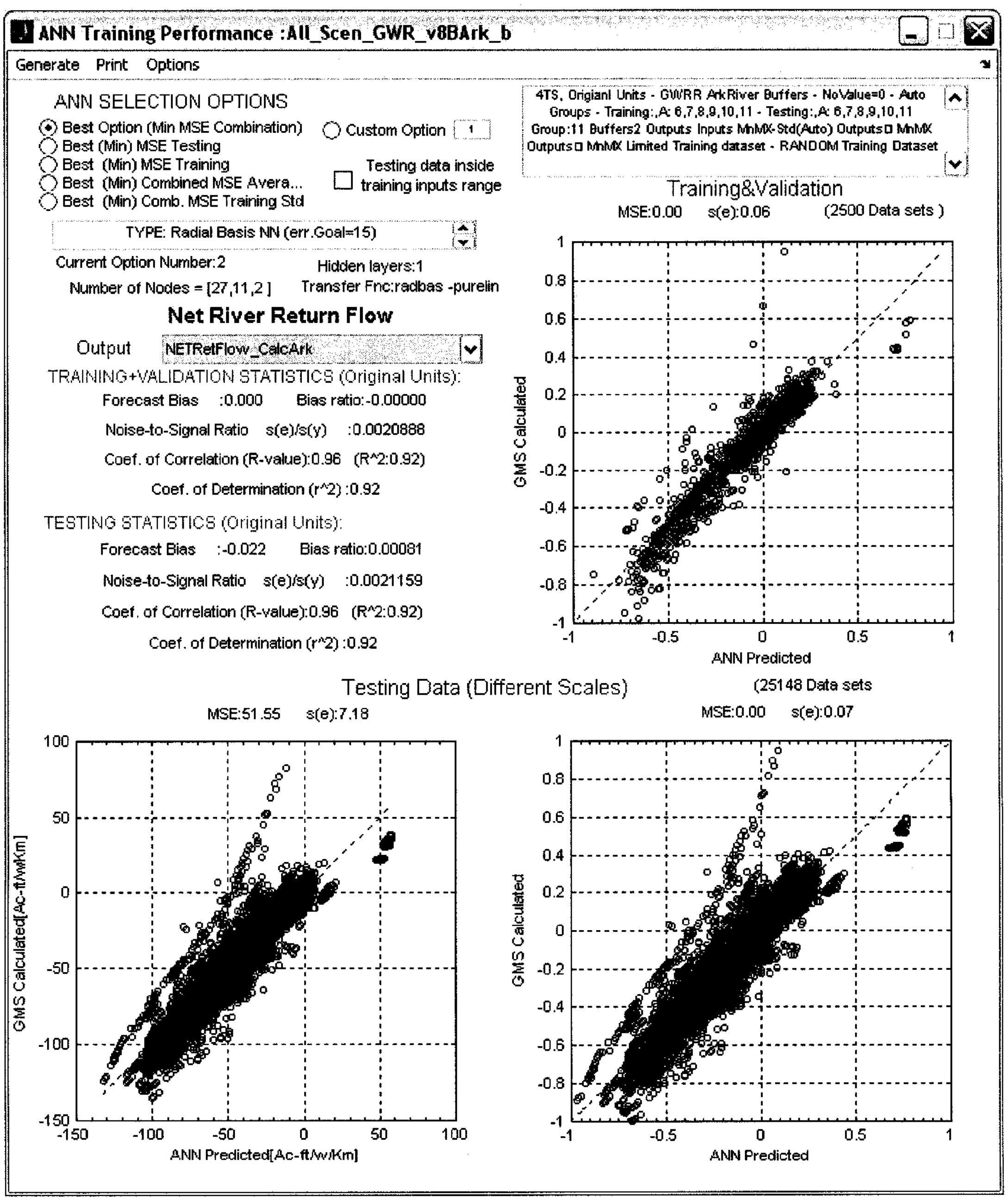


Figure 4.18 – All_Scen_GWR_v8Ark_b ANN training\testing performance

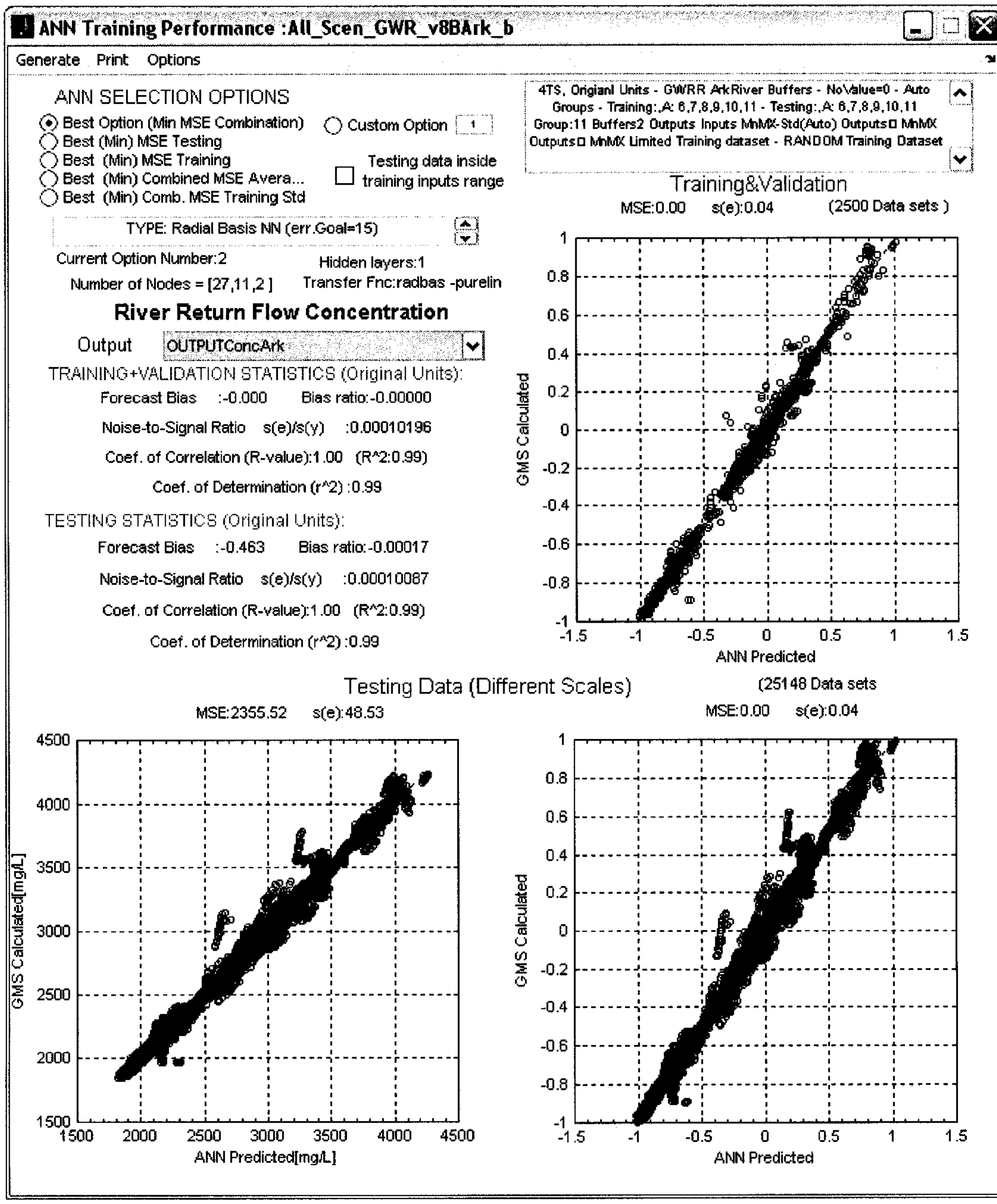


Figure 4.19 – All_Scen_GWR_v8BArk_b return flow concentration training and validation analysis

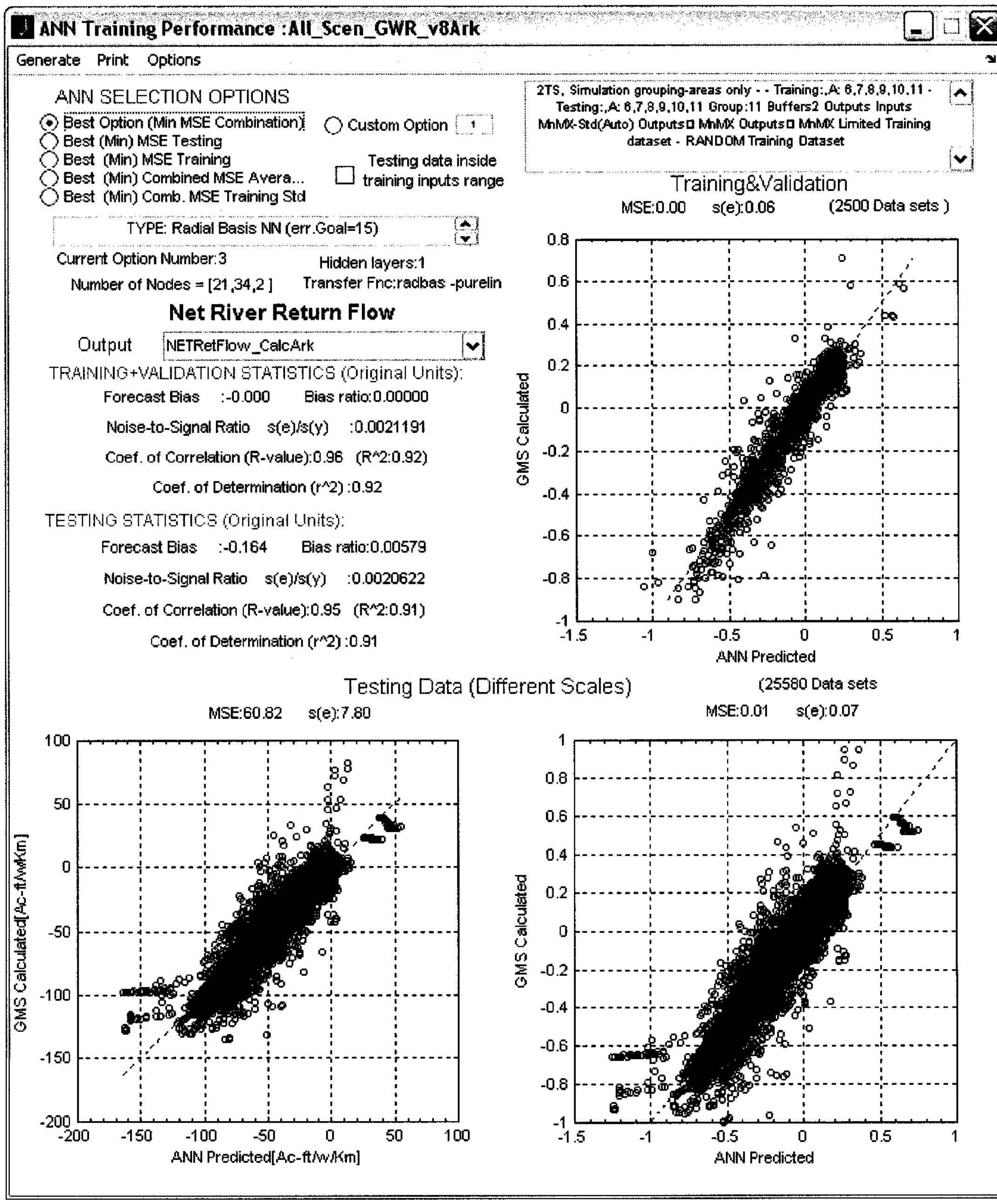


Figure 4.20 – All_Scen_GWR_v8Ark ANN training\testing performance analysis

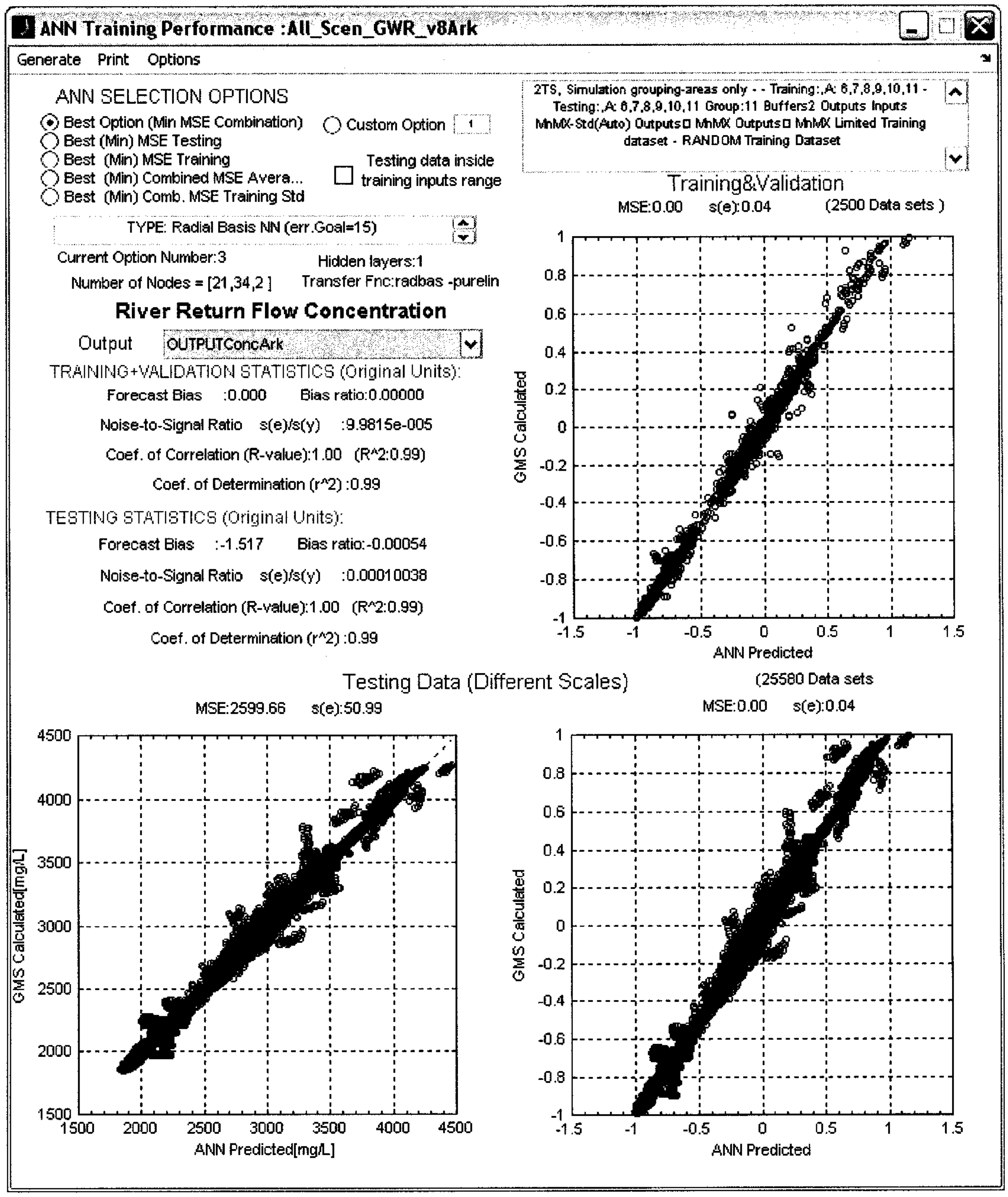


Figure 4.21 – Return Flow Concentration predicted by All_Scen_GWR_v8Ark

Tributaries Stream-Aquifer Interaction ANN

For the tributary stream-aquifer interaction ANNs, the explanatory variables are gathered from both available area-buffers to capture system stresses in areas far from the main stem but important to describe return flows to the near by tributaries. The variables made recurrent are only the output variables: (1) net return flow to the Arkansas River and (2) return flow concentrations. The return flow output is normalized per length of tributary streams marked with an active return flow flag in the corresponding grouping area. Two previous time steps of the return flows and their concentrations are used to provide data on time-varied influences. The training dataset excludes grouping area number 7 since it has a tributary length less than one kilometer. In addition, cases having tributary stream lengths or return flow concentrations equal to zero are excluded from the training. Data filters are also used in the testing dataset for realistic simulation performance measurements. These filters are handled when simulating with these ANNs in the *River GeoDSS* simulation tool.

ALL_Scen_GWR_v8BTrib_c Validation for Tributaries Stream-Aquifer Interaction

Figure 4.12 shows the preferences for the generation of the ANN training datasets using the Geo-MODSIM historical reservoir simulation (*Dataset_A*). The return flow prediction analysis shows good prediction ability of the tributary aquifer return flow (Figure 4.22). The computed coefficients of determination are R^2=0.97 and R^2=0.98 in training and validation respectively. The testing set mean squared error $s^2(e)$=5.67 (acre-ft/km)^2 and $s(e)$=2.38 acre-ft/km; the noise-to-signal ratio=0.003 and the forecast bias shows a negligible over-prediction $m(e)$=0.054 acre-ft/km. Figure 4.23 shows the *ALL_Scen_GWR_v8BTrib_c* ANN return flow concentration prediction analysis. The analysis show accurate predictions with high coefficients of determination of R^2=0.99 and $m(e)$= -1.87 mg/L; with a prediction root mean square error of $s(e)$=46.4 mg/L.

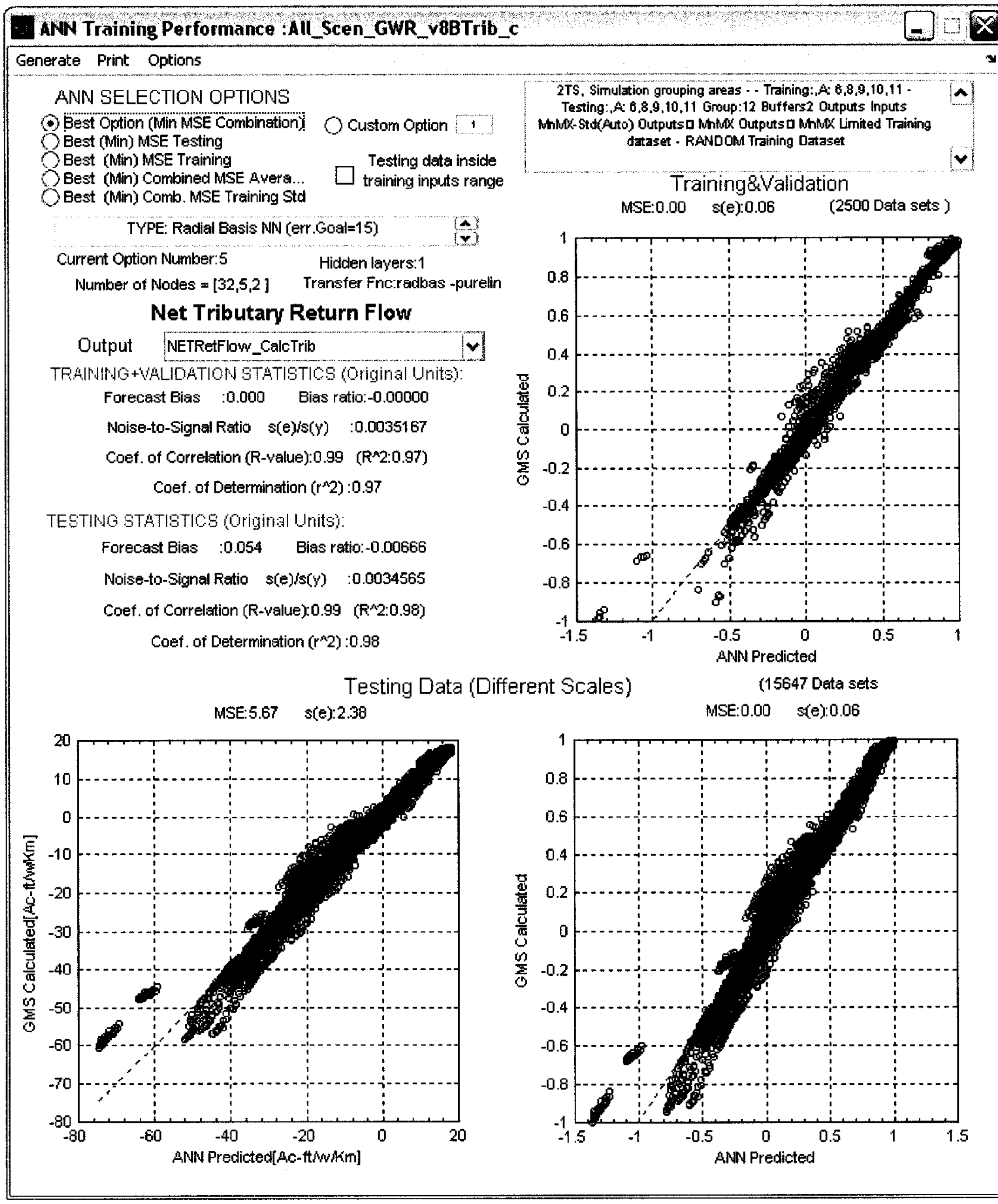


Figure 4.22 – All_Scen_GWR_v8BTrib_c return flow prediction performance analysis

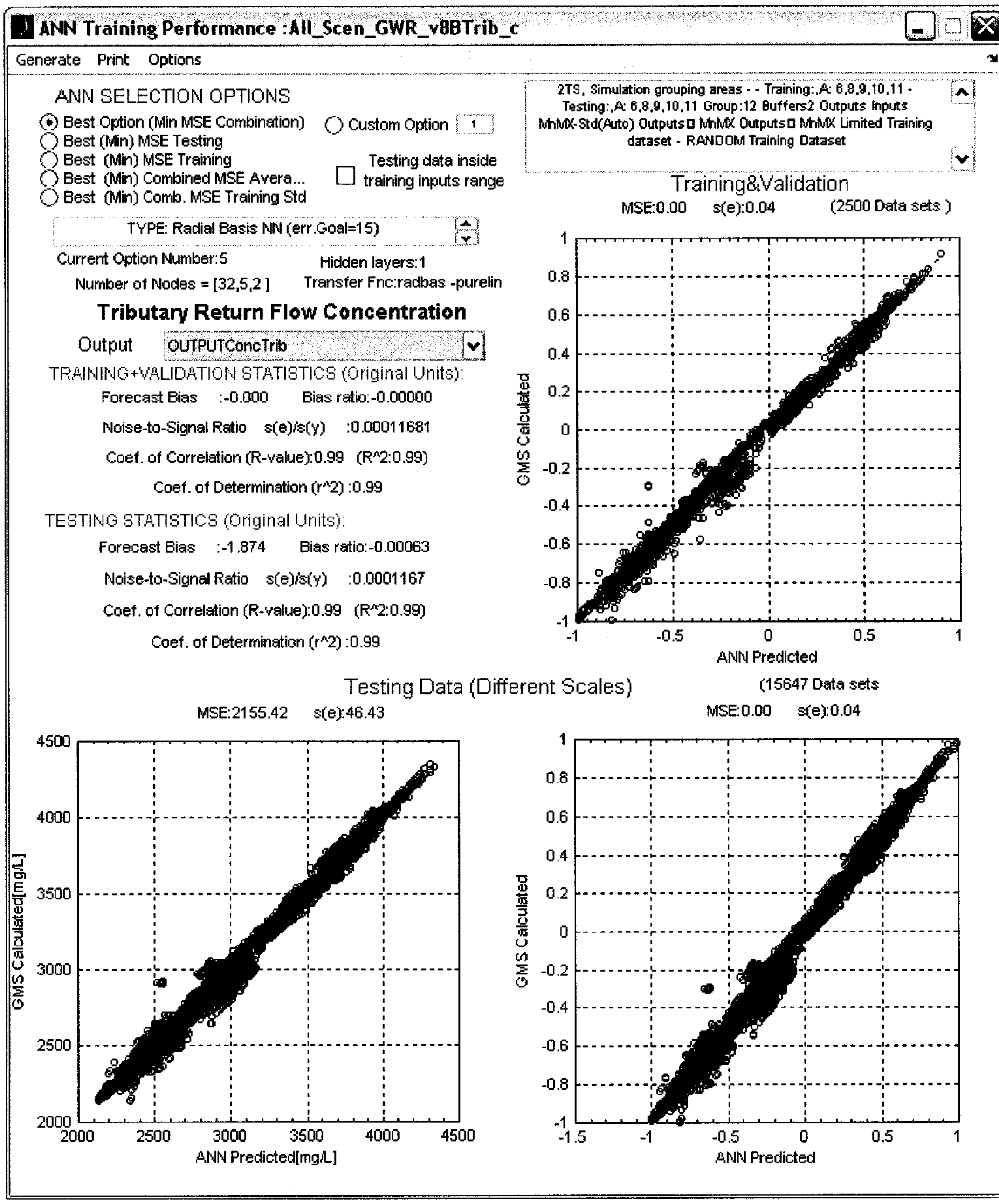


Figure 4.23 – All_Scen_GWR_v8Trib_c return flow concentration prediction performance analysis

ALL_Scen_GWR_v8Trib_a Validation for Tributaries Stream-Aquifer Interaction

This Neural Net is trained to predict the tributaries stream-aquifer interaction using *Dataset_B*. Figure 4.24 shows the preferences used to build the training dataset for this ANN.

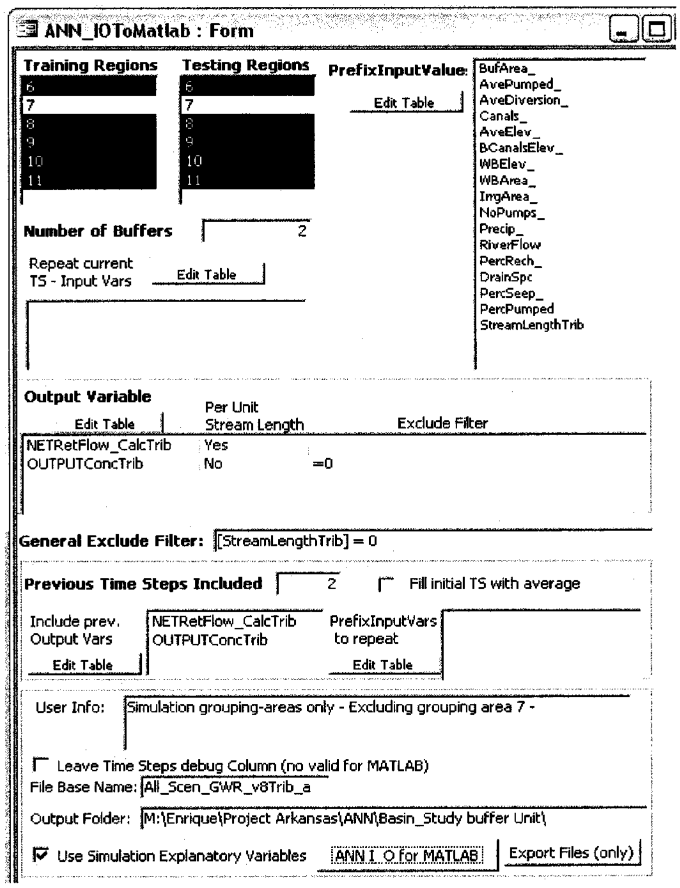


Figure 4.24 – ANN training dataset preferences for aquifer-tributary interaction modeling with Dataset_B

The ANN prediction performances are analyzed on Figures 4.25 and 4.26. The prediction statistics show an accurate return flow prediction with R^2=0.98 in both training and validation; $s(e)$=2.18 acre-ft/km; the noise-to-signal ratio equals 0.003 and $m(e)$= -0.09 acre-ft/km. The return flow concentration results give R^2=0.98; $m(e)$ =1.88 mg/L; and $s(e)$=69.2 mg/L.

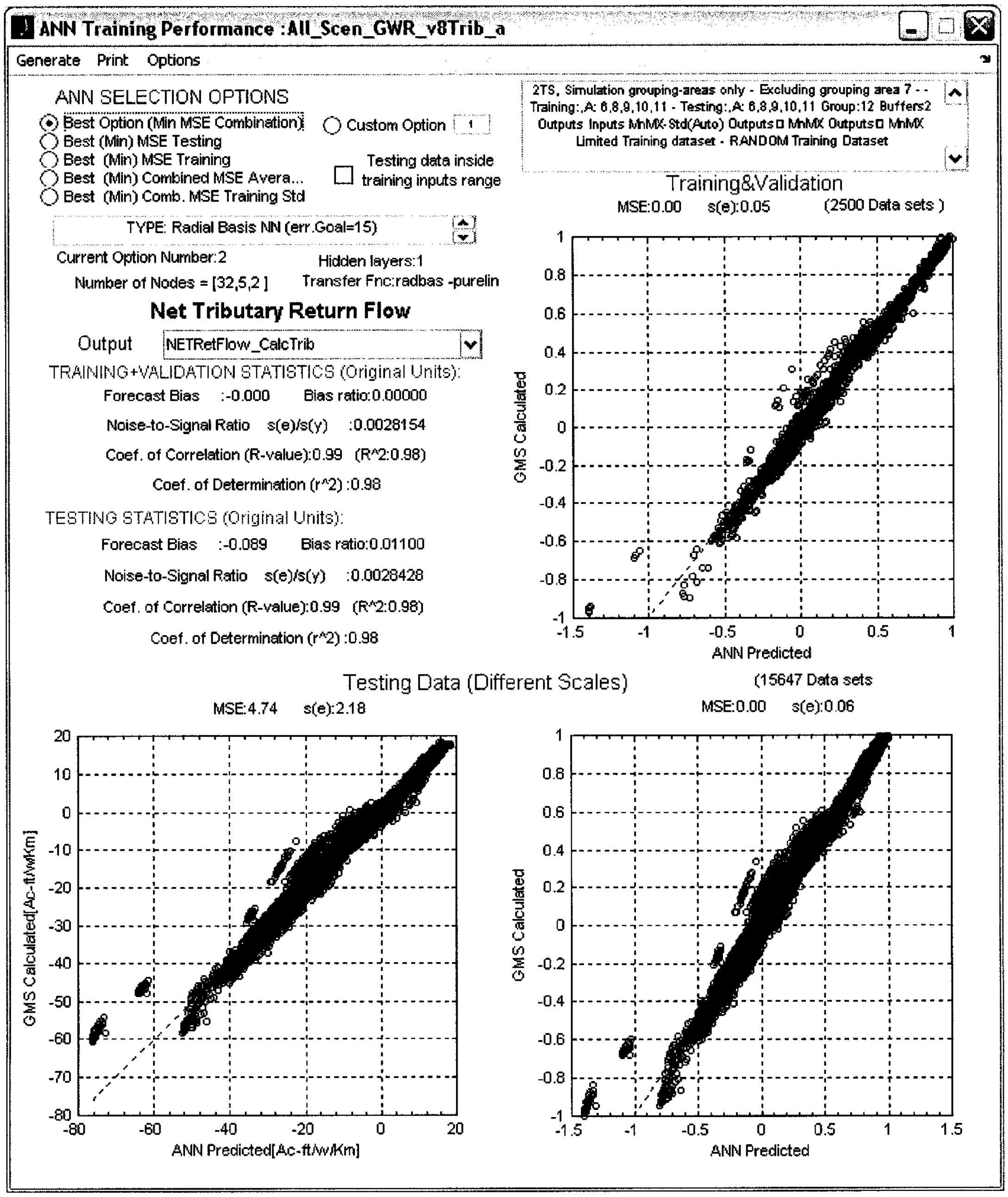


Figure 4.25 – All_Scen_GWR_v8Trib_a return flow prediction performance analysis

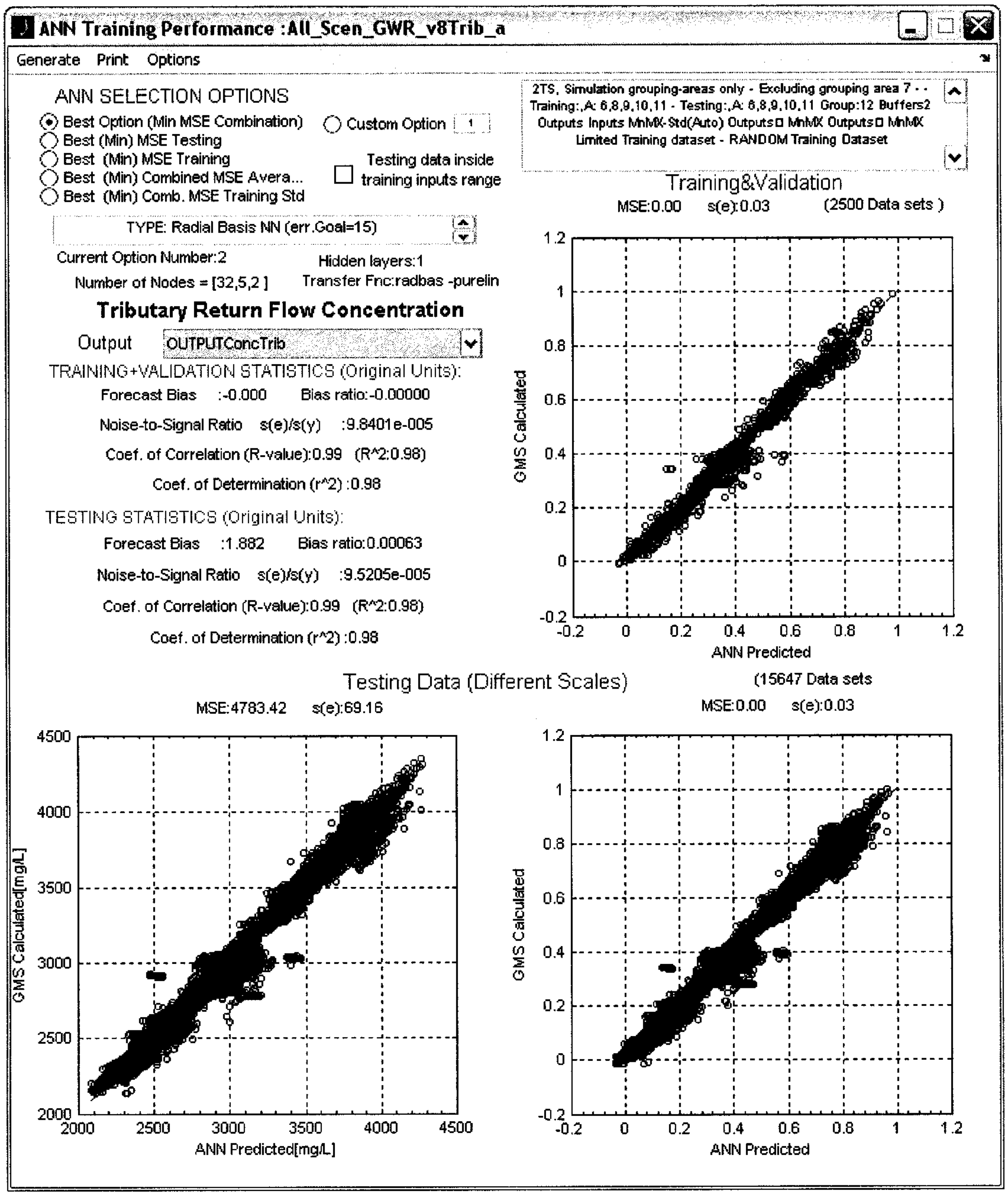


Figure 4.26 – All_Scen_GWR_v8Trib_a return flow concentration prediction performance analysis

ANN Performance Evaluation

The trained ANN performances are evaluated in detail on the baseline and some selected management scenarios. A set of interactive MATLAB-based reports are implemented in the custom ANN training tool to compute and display the predictions for analysis and comparison with observed values (i.e., modeled values in this case). This evaluation consists of comparison of predicted and modeled values for both return flows and concentrations at several detailed levels. The first level is overall performance including all simulated scenarios, along with the baseline, and all modeled grouping areas. The next level is performance evaluation for all grouping areas in the baseline scenario. The final level includes prediction comparisons for each individual grouping area. Appendix II presents the baseline detailed performance evaluation for the four trained ANNs for stream-aquifer interaction modeling and selected comparisons of the prediction for the management alternatives as compared with the baseline prediction.

ANN-based Stream-Aquifer Modeling Analysis

The methodology for stream-aquifer interaction modeling based on artificial neural networks as introduced herein is demonstrated as a robust alternative to traditional methods such as the SDF method (Jenkins 1968) or MODRSP approaches (Maddock and Lacher 1991). Congruent with Suen and Eheart (2003), the ANN type selection gave preference to the radial basis networks to represent complex problems. In this study, the radial basis ANN succeeded in modeling an extremely complex phenomenon with the simplest network architecture, while performing exceptionally well in the overall prediction of the large number of testing cases, including the management scenarios. The largest errors are located at the initial time steps of the groundwater simulation where erratic behavior is visible in the modeled values. The trained ANNs are able to closely duplicate the MODFLOW modeled return flows per grouping area and the corresponding MT3DMS modeled concentrations. Therefore, the trained ANN can be used to substitute the groundwater model in the *River GeoDSS* for conjunctive use modeling. The main advantages of implementing the trained ANN in the *River GeoDSS* modeling system (often referred to as "machine learning" approach) are: (1) the ANNs are able to predict return flows and concentrations faster than a finite difference model, (2) the predictions based on this methodology avoid compromising the quality of the predictions with approximations; e.g., linear superposition, as would be required in simplified groundwater modeling methods (Glover 1974; Jenkins et al. 1972; Maddock and Lacher 1991), (3) its design allows applying the learned relationships between system state changes and stream-aquifer system response in contiguous areas that lack detailed groundwater models.

Traditional coupling between groundwater and surface water models for conjunctive use modeling can be performed directly if the groundwater model covers the basin modeled area and all the simulated alternatives are modeled in the groundwater model. This unique approach can be used to substitute the MODFLOW-MT3DMS groundwater models in their coupling with MODSIM by not only replacing the groundwater model in the modeled area, but also predicting stream-aquifer interactions (1) for areas where groundwater models are unavailable, and (2) for management alternatives not included in the groundwater model. This approach allows conjunctive use basin scale modeling in the Lower Arkansas River Valley, where detailed groundwater models are not available for the entire basin.

The trained ANNs for the two reservoir operations do not show significant differences in predictions performance. It can be concluded that using more than two weeks of memory only marginally improve, if any, the prediction performance and can cause larger error-accumulated effects on the simulation.

Uncertainty Discussion

The developed ANN attempts to reproduce the MODFLOW-MT3DMS modeled stream-aquifer interaction, and therefore inherits all the uncertainty associated with the groundwater model in predicting the stream-aquifer interaction. Additional uncertainty is introduced by the implemented methodology, with the main sources of uncertainty in the ANN representation of the groundwater model being: (1) discrepancies between the values calculated for the regional-scale groundwater model and the homologous variables computed for ANN training (e.g., pumping, precipitation, canal seepage, recharge), (2) the spatial aggregation of variables and predictions, (3) differences in stresses due to shifts in weekly time steps between MODSIM and MODFLOW-MT3DMS (after the second year of simulation there is a shift between stresses and responses), and (4) the ANN model structure and error goals. Statistics on the reports included in Appendix II give a sense of the uncertainty associated with the ANN predictions.

Non-Modeled Areas Prediction

In addition to uncertainty in the modeled area, additional uncertainty is introduced while using the learned relationships outside the groundwater modeled area. Since the ANN is trained based on conditions that might be unique for the modeled area, such as aquifer characteristics, the assumption for basin scale application is that those unique characteristics are not going to significantly change in the non-modeled area to as to invalidate the predictions. Based on this assumption, the uncertainty is potentially going to increase with distance between the modeled area and the prediction location. John Martin Reservoir, located downstream of the groundwater modeled region, could influence system characteristics in the downstream area by increasing the prediction errors in this region. Assessment of these errors is only possible if there are data available to compare against the prediction. Statistics could be derived removing by individual grouping areas from training and assessing the prediction errors. Since the modeled grouping areas are all clustered together, however, the ultimate error evaluation is only possible when the calibrated transient model for the downstream area becomes available. Analysis and validation of the baseline predictions outside the modeled area is performed using surface water measurements in the Arkansas River basin scale modeling presented in Chapter 7.

Limitations and Additional Thoughts

Since the ANN combines the effects of the explanatory variables to predict the stream-aquifer system response, these predictions are biased by the hydrologic conditions for which the network was trained. In this case, the groundwater modeling encompasses the transition from an extremely wet period to a drier period. Therefore, the predictions are expected to behave in a similar fashion to the aquifer response under these conditions. The magnitude and sequence of the explanatory variables will dictate, to some degree, the prediction but it must be noted that the underlying behavior was a wet-to-dry transition.

Reservoir Water Quality Transport Modeling

Valerie (2001) analyzed the regional transport of water and dissolved constituents through heavily regulated river systems, showing that the system is influenced in varying extents by the presence of reservoirs. Transport of chemicals through heavily regulated river systems is influenced by the interaction between the chemistry of the inflowing water and processes occurring within reservoirs. These processes are determined by (1) reduced water velocities and concomitant loss of sediment, (2) the timing and extent of thermal stratification, (3) advective transport characteristics and the occurrence of density currents, (4) the location of outflow portals, (5) hydraulic retention times, and (6) biological activity within the reservoir (Thornton et al. 1990). Additionally, concentrations of dissolved materials from evaporation is a major factor in controlling salinity in reservoirs due to increased residence time, temperature, and surface area, especially in arid basins. Accurate basin scale water quality modeling with in-line reservoirs requires the modeling of these processes in the reservoir. Modeling the complex processes in the reservoir, using the most up-to-date tools such as CE-QUAL-2E (Wells 2000b), requires a large number of input variables and detailed information on the reservoir system that is not readily available. A need for a simplified but robust approach is identified to assist the basin scale salinity modeling efforts of this research project.

John Martin Reservoir Salt Transport Analysis

Salt transport in John Martin Reservoir is analyzed based on available historical data from November 1985 to October 2004. The two stations providing water quality data on inflows include ARKLASCO and PURLASCO, with the ARKJMRCO station providing continuous records for water quality of the reservoir outflows. The ARKLASCO station is located on the Arkansas River, and it records data regularly at constant time intervals, whereas the PURLASCO station is located on the Purgatoire River and has intermittent total dissolved solid samples. The TDS samples at PURLASCO are used to fit an equation to represent concentrations as a function of the flow during periods where no data are available. The data indicate a wide range of concentrations for a given flow (especially low flows), with the best fit equation from the set of tested equations determined to be logarithmic (Figure 4.27). Since this equation shows an extremely low portion of the variance as explained by flow, indication that there exist additional factors that influence concentration measurements at the station. For this demonstration, the concentrations are assumed to result from the fitted logarithmic equation.

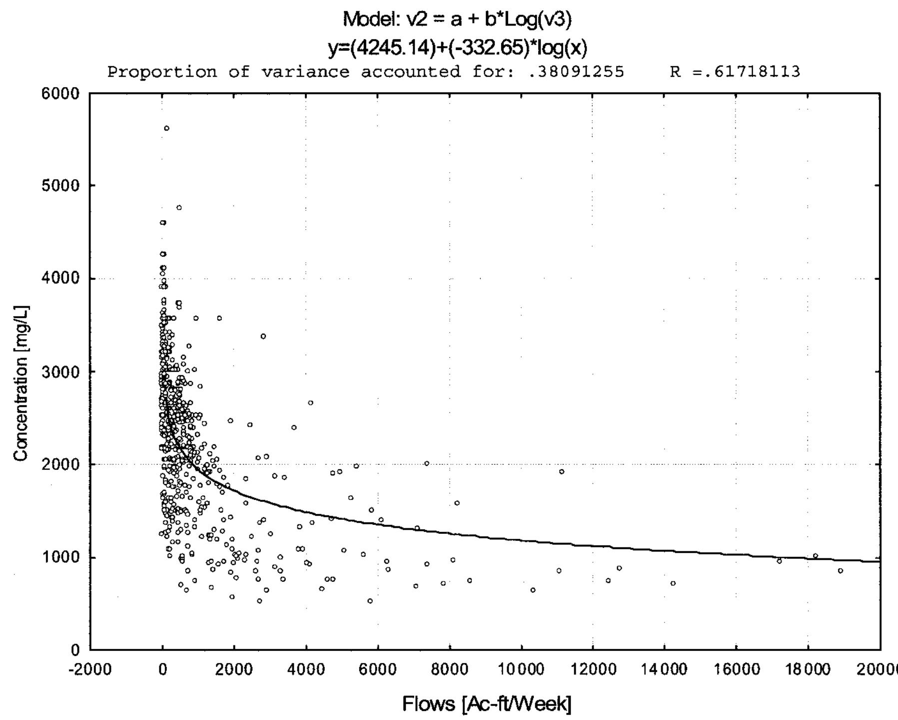


Figure 4.27 – Flow vs. Concentration at Purgatoire River near Las Animas

Results from Valerie (2001) indicate that sites located above the major reservoirs on the Colorado River and the Rio Grande have different characteristic and distinct chemical signatures, with passage through the reservoirs acting to merge and collapse these individual signatures. Figure 4.28 shows a comparison of the combined salt load coming into the reservoir from the Arkansas and Purgatoire Rivers and load coming out the reservoir to the Arkansas River. This figure shows a seasonal behavior, in which during the irrigating season (peak flows), the salt mass released from the reservoir is greater than the salt mass coming into the reservoir; conversely, the salt mass conveyed downstream during the non irrigation season is smaller than the mass load entering the reservoir. In addition to the increased evaporation occurring during the summer months, it appears that the high flow season increases the reservoir layer mixing and therefore contributes higher salt mass loadings downstream. The aggregated annual salt transport is summarized in Figure 4.29, showing that the net salt mass entering/leaving the reservoir changes from year to year. Figure 4.30 shows that the addition of salt to the reservoir is correlated with the net increase in storage (positive *TotalFlowIn*).

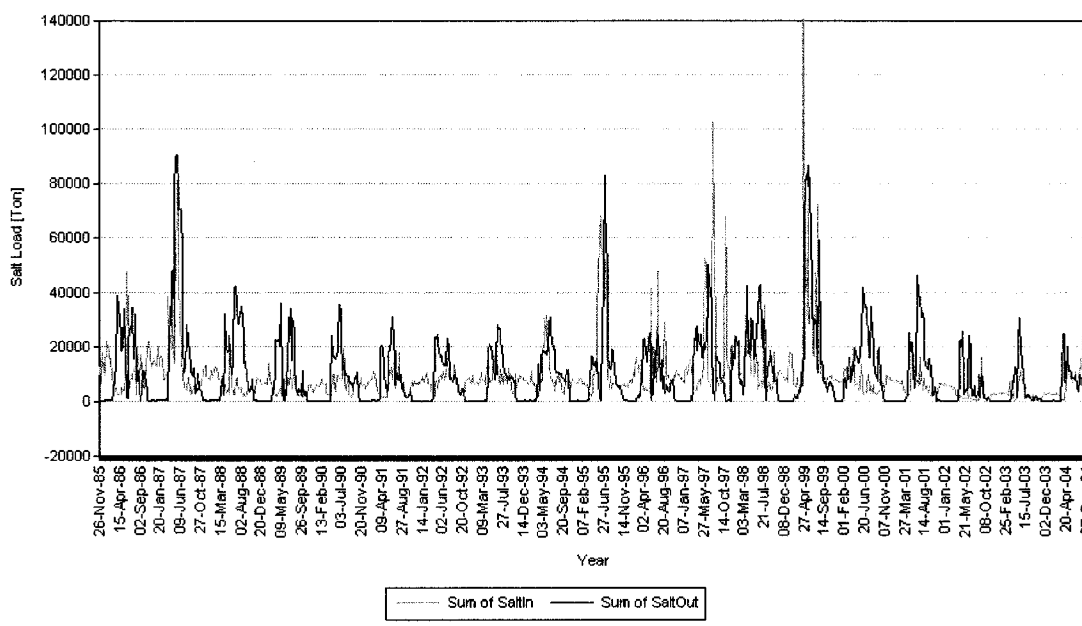


Figure 4.28 – Salt transport in John Martin Reservoir

Analysis of salinity concentrations reveals a different behavior than the salt loadings. Salinity concentrations of the reservoir inflows fluctuate more than the outflow concentration, indicating that the reservoir performs a smoothing effect on the concentrations. Figure 4.31 shows the Arkansas and Purgatoire inflows concentrations, along with the John Martin Reservoir outflow concentrations. In general, the Purgatoire concentrations are larger than the Arkansas concentrations, with corresponding averages of

2608.08 mg/L and 2168.56 mg/L respectively. Concentrations of the outflows are less variable and average 1861.83 mg/L, showing an overall reduction in concentration for the analyzed period.

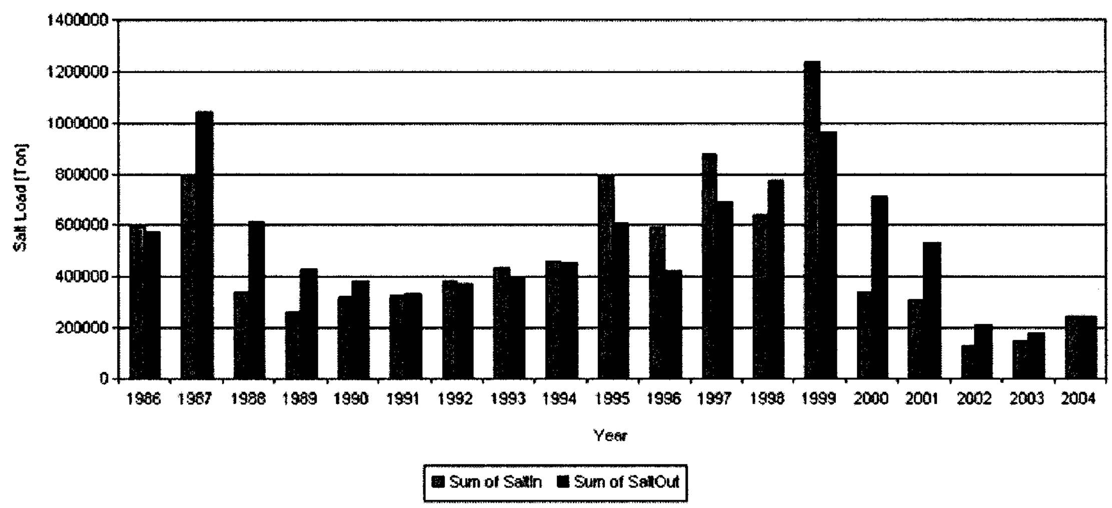


Figure 4.29 – Annual Salt Load In/Out John Martin Reservoir

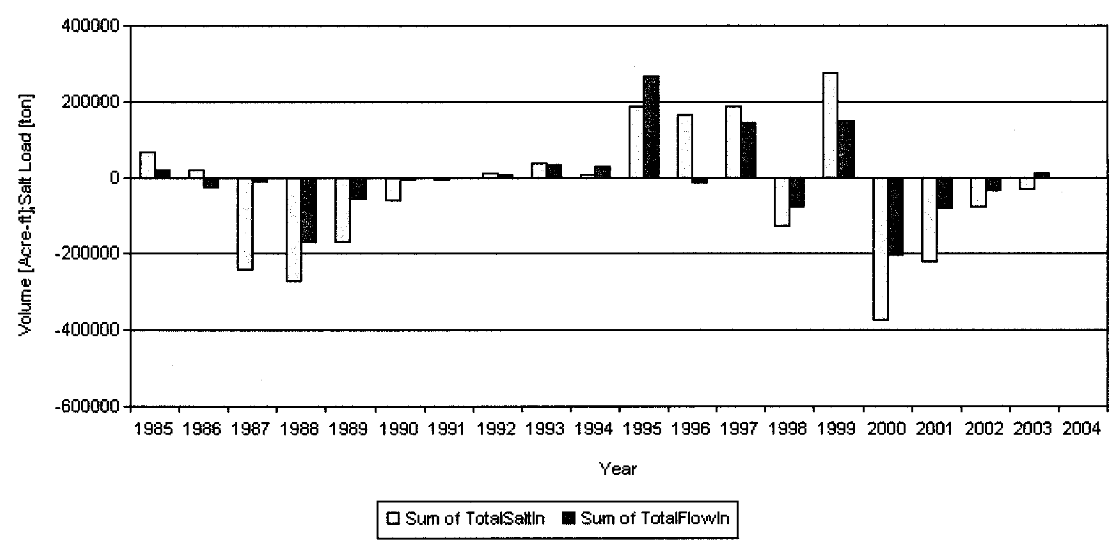


Figure 4.30 – John Martin net annual change in storage and salt mass

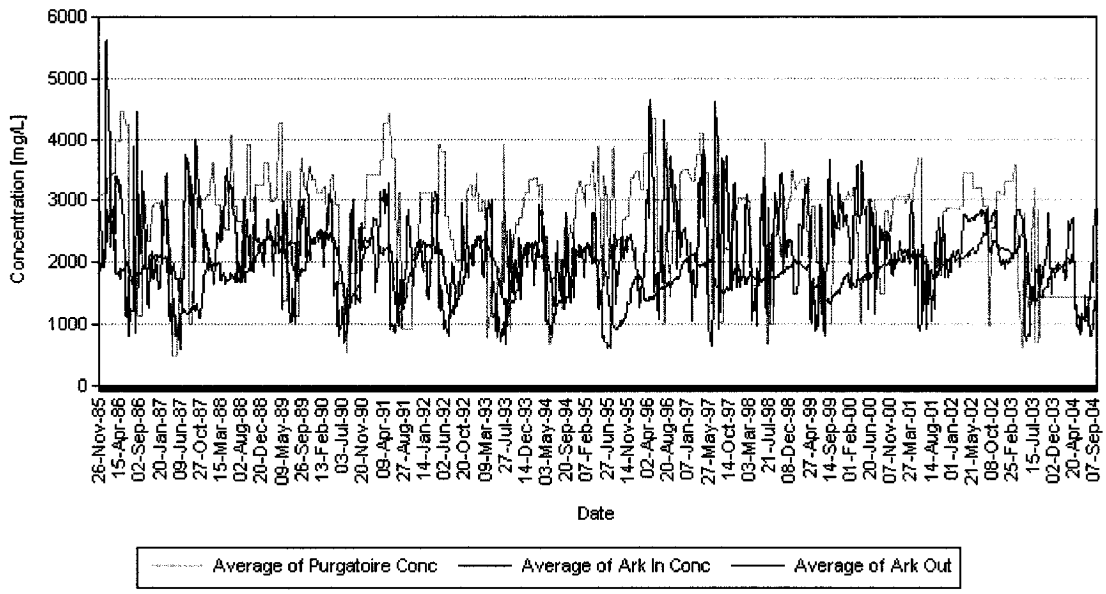


Figure 4.31– John Martin Reservoir concentration In\Out

Concentrations at the outlet of the reservoir are consistently lower during the high flow seasons, and inversely correlated to the salt loadings. Observing the historical data, there is a clear tendency for low concentrations to occur right after a high flow season has began. Low concentration values for the reservoir outflows show a strong lagged-relationship with peak discharges (Figure 4.32), pointing to a significant lagged correlation between them.

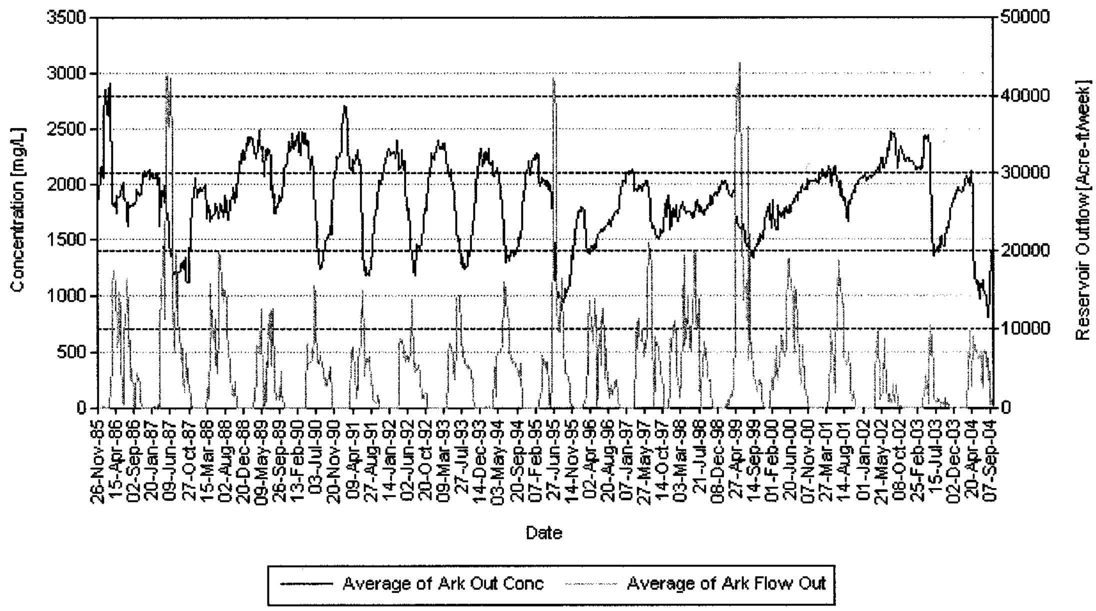


Figure 4.32 – John Martin Reservoir outflow and concentration

A cross-correlation analysis was performed between the measured variables at the inlets and outlet of the reservoir. The reservoir release (*ARKJMRCOSurfIn*) and the outflow concentration (*OUTPUTInRiver*) cross-correlation corroborated the observed strong correlation between these two variables (Figure 4.33-A). The statistical analysis also illustrated a strong autocorrelation of the reservoir outlet concentrations. The results show significant correlations up to 15 lags (weeks) based on values higher than 0.7 up to the first 6 lags (Figure 4.33-B).

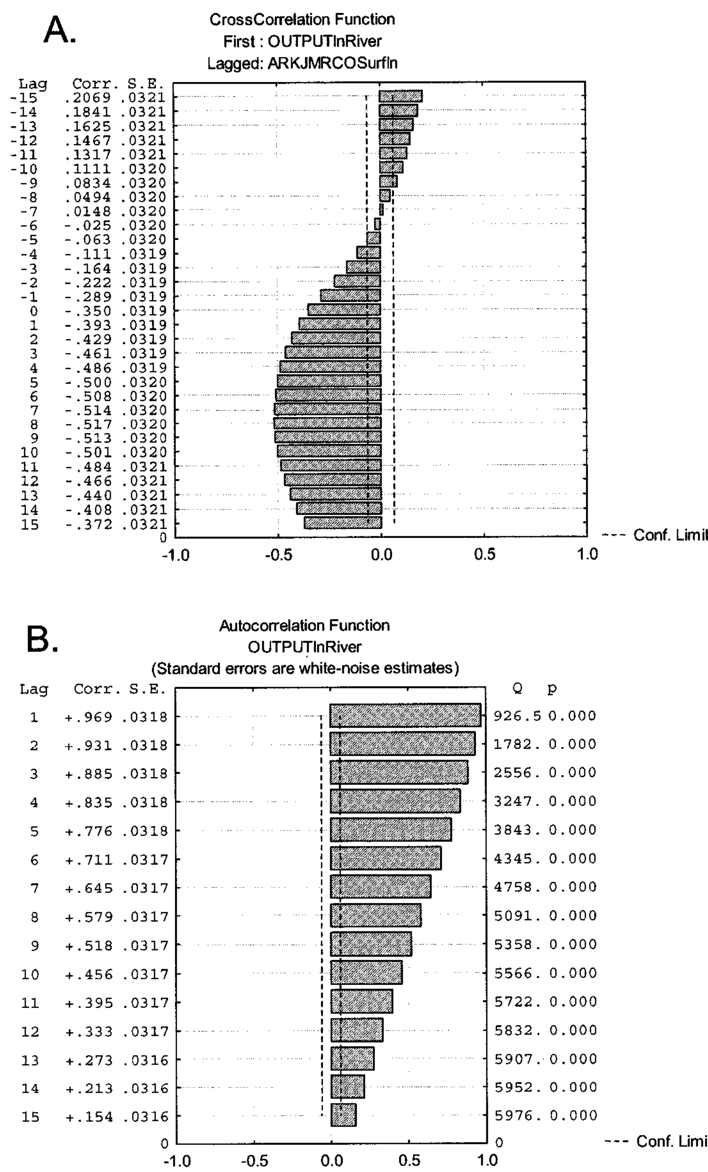


Figure 4.33 – Outlet variables correlations

This analysis reiterates the necessity for modeling salt transport through John Martin Reservoir to better quantify water quality effects of management alternatives in the LARV downstream of John Martin.

Approach

An ANN-based approach is proposed to model salt transport through John Martin Reservoir, which avoids simplifications that would relax the data requirements and modeling complexity. The ANN-based modeling approach is rooted in measured reservoir states, inputs and outputs by attempting to match the historical overall results based on a full range of processes occurring in the reservoir. The ANN model is designed to describe average weekly output concentrations as a function of the reservoir inputs (i.e., flow and salinity loadings), reservoir releases and changes in storage. The weekly explanatory variables for the outlet concentrations are the flows and concentrations at the Arkansas and Purgatoire Rivers near Las Animas (Colorado), the beginning and ending reservoir storage for each simulated week, and the corresponding reservoir release. The explanatory variables include selected previous week inputs and outputs as time-varying "memory", taking advantage of the observed lagged correlation/autocorrelation.

ANN Development

A training dataset is created from the weekly processing of the available measured data using the fitted curve to represent concentrations in the Purgatoire River. The dataset is created processing measured values for the weeks in three periods: (1) from 01/1980 to 03/05/1999, (2) from 03/05/1999 to 08/2003, and (3) the weeks from 04/01/99 to 10/14/01 (weeks shifted from data group 2); the cases are flagged with a group identifier using the field *RetHydroID*. The first and second groups are to be used for ANN training and validation; the third group will test the NN performance on a shifted weekly data set to observe sensibility to the weekly groping of variables.

ANN Database Management Tool

A customized version of the *ANN Database Management* tool is implemented for John Martin salt transport modeling. The MS-ACCESS user interfaces are used to generate the MATLAB ANN training/testing files. Figure 4.34 shows the preferences for building this ANN training dataset. Three previous weeks of outlet concentrations, reservoir ending storage and Arkansas flow entering the reservoir are used to simulate a recurrent effect allowing the neural net to use time-varying patterns in the predictions. Using these preferences, the Database Management Tool creates the set of files for MATLAB ANN training.

ANN Training

Relationships between the explanatory variables and the outlet concentration were searched training different types of ANN and performing multi-variable regression analysis, with the Elman NN producing the most robust and consistent set of predictions. The network is trained using a time-sorted dataset of 920 cases (2/3 of the training dataset) and tested/validated with the remaining 307 cases. The testing/validation dataset mainly corresponds to cases in the second group of the dataset (flagged with *RetHydroID* = 2). The training was performed using the *River GeoDSS* custom MATLAB Training Tools with 10 training sessions of 15 trainings each. For each training event, the network is built with a single hidden layer with random number of neurons (maximum 45 neurons) and random transfer functions. For each session, the representative network is the one with best combined performance (Equation 4.1). In agreement with the autocorrelation analysis, the inclusion of previous outlet concentrations is demonstrated to positively influence the predictions. The Elman Network training time for these sessions is much longer than similar training of the standard feed forward ANN. From all the sessions, the best combined performance ANN has 32 neurons and two tan-sigmod transfer functions. Figure 4.35 shows the ANN performance during training and testing/validation for the best training event.

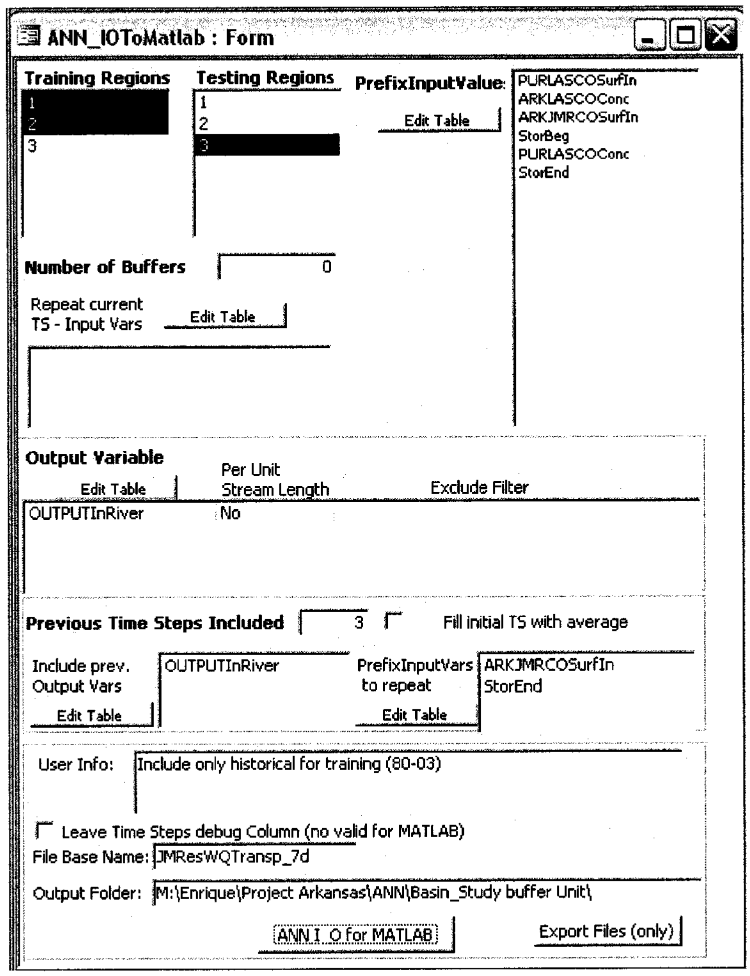


Figure 4.34 – John Martin Reservoir salt transport ANN training dataset preferences interface

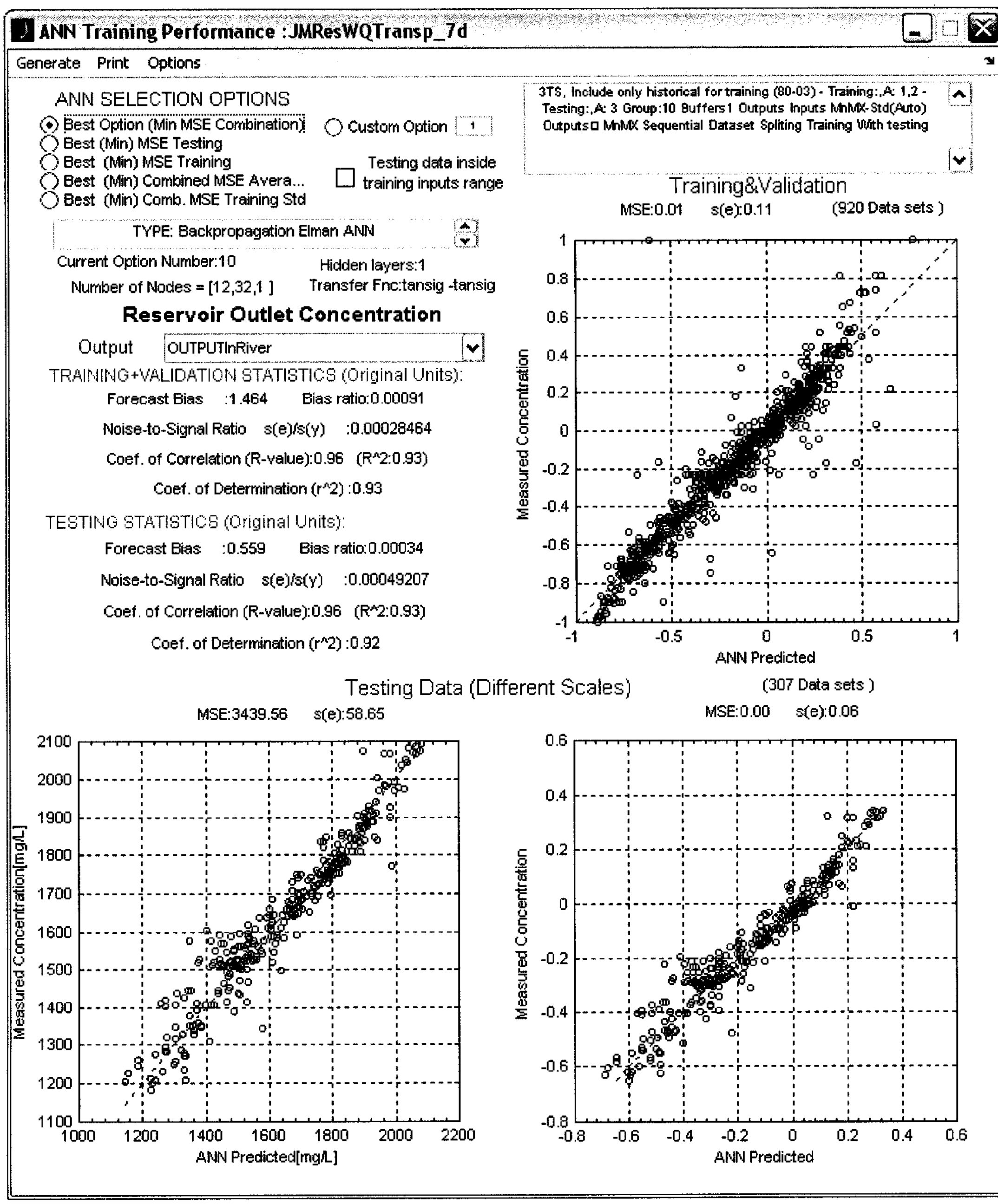


Figure 4.35 – ANN training and validation performance summary for the John Martin Reservoir salt transport

The predictions show a coefficient of determination of 0.93 and 0.92 in training and testing respectively, with a testing prediction root mean squared error of 58.5 mg/L, indicating a good ability to predict the John Martin outlet concentration. The predictions were tested in the same original test period with the modeled weeks shifted to observe the explanatory variables sensibility. Figure 4.36 shows the MATLAB-based performance report in the modeled weeks from 4/1/1999 and 10/14/2001. The calculated coefficient of determination (0.93) and the root mean squared error (58.16 mg/L) indicate little sensitivity to variations in the weekly-grouped explanatory variables. Application of the Elman ANN with the generated training dataset combines the dynamic feedback from the previous hidden layer output (Elman ANN) with a static feedback from the previous outputs as included in the training dataset (similar to a Jordan ANN (Jordan 1990)).

Reservoir Outlet Concentration Modeling Analysis

Most of the approaches reviewed in the literature deal with detailed hydrodynamic and chemical reservoir modeling (Willey et al. 1996; Bicknell and National Exposure Research Laboratory (U.S.) 2001;). The newest tendencies in reservoir modeling development point to an increase in detail and dimensionality (Hamilton and Schladow 1997). The input-output mapping approach allows development of robust tools for modeling the highly complex processes in reservoirs, as demonstrated in the application of ANNs management of eutrophicacion in lakes (Karul et al. 1999;Walter et al. 2001). The methodology introduced herein to model reservoir outlet concentrations provides a unique approach, with the explanatory variables selected to model salt transport appearing to provide the ANN with sufficient information to mimic the historical concentrations of the reservoir releases. The model application to John Martin Reservoir transport modeling shows robust predictions outside of the periods where the neural network was trained, giving confidence in its application as predictor during management scenarios modeling (events not available in the historical dataset).

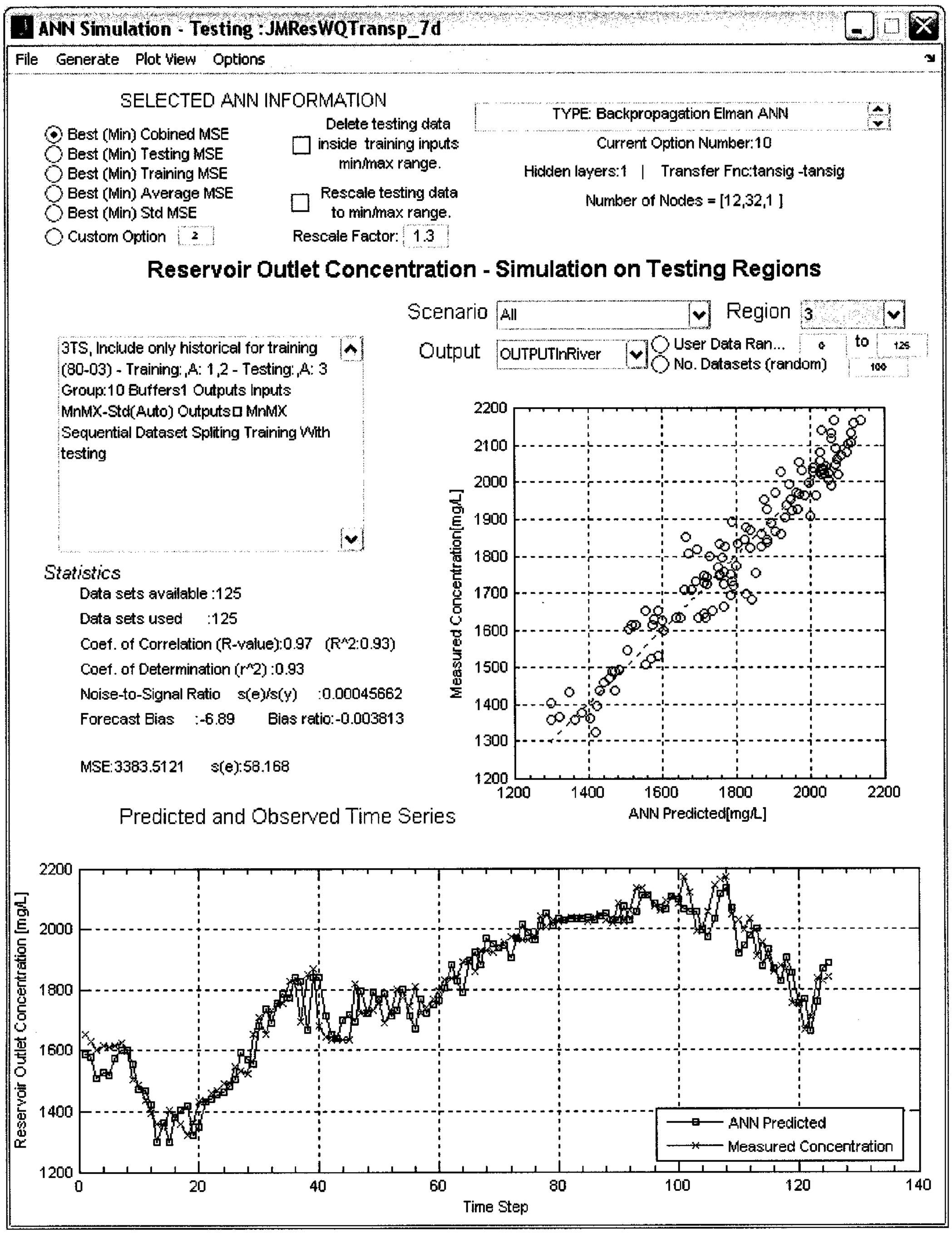


Figure 4.36 – John Martin Reservoir Outlet concentration ANN prediction in testing

The developed model finds relationships between reservoir inputs, state and their outcome in time, making the model utilization quick and suitable for integration in basin scale management decision tools. Although the ANN models developed with this methodology are expected to be specific for the reservoir they are developed for, it is believed that the application of the methodology is suitable for modeling other reservoirs and could be extended to model other water quality parameters.

The Simulation Challenge

The ANN-based models introduced in this chapter were developed with the idea of being integrated into a comprehensive basin scale decision support tool. Differences between the training and simulation dataset are expected to affect the performance during simulation. An anticipated challenge of this integration is the use of "imperfect" explanatory variables. The training was performed with datasets that use explanatory variables from "perfect" previous predictions (prediction with no error). A sequential simulation with the trained ANN will use explanatory variables with an implicit error from previous predictions uncertainty; in addition to the new uncertainty added using this simulation dataset, the risk is that the error accumulates making the deviation on the recurrent explanatory variables to grow incontrollable during the simulation progress, resulting in unrealistic ANN predictions. In an attempt to minimize the discussed effect, the selection of the best ANN to predict the modeled phenomena included testing of performance with sequential previous outputs. Neural networks that showed high sensitivity to the recurrent explanatory variables error accumulation in sequential simulation were discarded. The number of previous time steps explanatory variables was set to the minimum without compromising performance. The rationale is that the more previous time step outputs included the more uncertainty in the explanatory variables.

Another ANN simulation challenge deals with the initial recurrent explanatory variables. In the stream-aquifer modeling, the NNs will predict return flow and concentration in areas were there is not groundwater modeling available and periods outside the groundwater modeled period. Therefore, in these cases there are not pre-existing output variables for building the explanatory variables set. The recurrent explanatory variables for the initial time steps will influence the sequence of predictions space; therefore in simulation, setting these variables could play a key roll in the successful implementation of the stream-aquifer interaction modeling.

Lastly, some explanatory variables might get adjusted during the basin scale simulation causing discrepancies between the training and the simulation. ANN inputs variables relying on flow, diversions, reservoir storage might deviate from their training counterpart. This is another example of issues that ought to be address while incorporating these ANN models in the *River GeoDSS* modeling system.

CHAPTER 5

CONJUNCTIVE GROUNDWATER AND SURFACE WATER QUANTITY AND QUALITY MODELING APPROACH IN *RIVER GEODSS*

STREAM-AQUIFER INTERACTION MODELING APPROACH

A common practice in the analysis and modeling of basin scale stream-aquifer interaction is an excessive simplification due to the cumbersome development of detailed models at this scale. Analytical approaches primarily rely upon a number of conceptual simplifications, thereby increasing the uncertainty and inaccuracy of the results [e.g., the CALVIN model (Howitt 1999)]. Common assumptions include simplified aquifer geometry and significant constraints on aquifer physical characteristics such as homogeneity, isotropy, time invariance, and infinite (or semi-infinite) aquifer extent. In contrast, finite difference and finite element numerical methods can accurately represent the time-variant, heterogeneous physical system, but are computationally intractable when appropriately applied over large areas.

A popular method to model stream-aquifer interactions at the basin scale is the stream depletion factor (SDF) method (Jenkins 1968). The SDF is a spatially variable system descriptor with time dimension, which indicates the time it takes for 28% of the depletion (or return flow) to occur, for predicting volumetric changes in streamflows due to recharge or withdrawal of water from the aquifer. The SDF method aggregates spatially-varied hydraulic properties, aquifer stress locations, and complex boundary conditions. Sophocleous (1995) compared the numerical finite difference model MODFLOW (McDonald and Harbaugh 1988) with SDF method and reported considerable discrepancies between the two approaches in representing a real-world stream-aquifer system. These results were corroborated by Fredericks et al. (1998), finding significant differences using groundwater response coefficients developed from the SDF method as compared to a finite difference groundwater model. The *River GeoDSS* includes tools required to directly link the MODFLOW-MT3DMS modeling cells comprising the finite difference grid with MODSIM objects, thereby taking advantage of the various geo-processing tools that can be applied on geo-referenced objects. However, this approach to conjunctive use modeling is considered impractical at the basin scale and therefore of limited use for evaluation of management alternatives. The methodology introduced herein represents stream-aquifer interaction at basin scale, but is founded on a regional-scale MODFLOW-MT3DMS groundwater modeling calibrated with extensive field data. Artificial neural networks are utilized to model the stream-aquifer interaction (as described in Chapter 4), with the trained ANN used to predict representative grouping area return/depletion flows and salt loadings. The methodology is computationally efficient and economically feasible, with an accuracy compromise as a function of the extent of the basin to be applied to outside of the groundwater modeled area.

Basin-Scale Water Quality Modeling

The use of relationships between flow and specific conductance, total dissolved solids and other ions (Cain et al. 1987; Sandhu et al. 1999) has been used to develop hydrologic water quality models in the Arkansas River basin. Cain et al. (1987) developed useful regression relationships between flow and specific conductance for several stations in the Arkansas River basin. This approach is limited, however, for accurately representing aquifer responses to management alternatives since the developed relations are based on historical events. These relations lack the ability to represent changes in system characteristics, which limits their use to the historical system conditions only. A more robust and comprehensive approach is sought for conjunctive use water quality modeling in the *River GeoDSS* to better handle management alternatives analysis that are not constrained to historical conditions.

The existing Arkansas River Valley MODFLOW-MT3DMS groundwater flow and water quality model takes into account the physical system characteristics and complex water quality constituents modeling in the unsaturated zone, allowing accurate prediction of system responses to management changes. Ideally, the *River GeoDSS* water quality modeling should include changes in the base-flow quality for management alternative comparison. Using the trained ANN stream-aquifer interaction model for management alternative simulation, it is possible to predict changes in groundwater contributions for both the main stem and the tributaries and analyze changes in base-flow conditions during these simulations. The most upstream water quality-measured points in the basin are modeled as water quality constituent sources. Baseline regression equations, similar to Cain et al. 1987, can be developed for the system sources and control points when only sporadic water samples are available. Even though the groundwater contributions will accommodate changes in the system dynamics during the simulation of the management alternative, the baseline regression equations assume that the same baseline conditions (i.e., all other flow and water quality constituent contributions) remain constant.

Conjunctive Surface-Groundwater Quantity and Quality Modeling

As the primary engine of the *River GeoDSS* Modeling subsystem, MODSIM provides great flexibility to accommodate complex operational aspects and provides the tools for realistic water resources system simulations under water rights and institutional constraints. In addition, the MODSIM version 8 modular design and .NET integration (Labadie 2006) allows coupling into other environments and models, thereby providing a flexible platform for enhanced modeling systems by attaching modules to the main model engine. In addition, the modular design allows development of customized graphical interfaces, such as the Geo-MODSIM interface described in Chapter 3. For example, the *River GeoDSS* Water Quality Module (WQM) providing conservative constituent modeling throughout the system, tightly linked with MODSIM flows and can interact with the ANN module to include its predictions in the water quality routing.

The *River GeoDSS* couples all its components to provide an innovative conjunctive groundwater surface water quantity and quality modeling platform. A trained ANN for stream-aquifer interaction (e.g., the ANN presented in Chapter 4) is made available in the modeling system through the *River GeoDSS* ANN Module. The ANN simulation dataset for all the modeled grouping areas is built into the *River GeoDSS* from the training files, system characteristics and MODSIM modeling variables. The ANN stream-aquifer modeling is incorporated into MODSIM by making use of the Geo-MODSIM spatial representation of the network. The Geo-MODSIM network is prepared to be coupled with the ANN by populating the data-model objects with: (1) a flag to indicate the type of ANN stream-aquifer modeling, i.e., main river or tributaries; and (2) the corresponding stream-aquifer modeling grouping area ID. The ANN provides water and salt accretion/depletion volumes per time step for each grouping area along the main stem and tributaries. These predictions are evenly distributed among the MODSIM nodes in each grouping area. The predicted flows and corresponding concentrations are incorporated into the MODSIM network using connecting links with an ANN source/sink support construct (as described in Chapter 3) where flows are provided to the MODSIM network as inputs and outputs of the system, where the predicted flows and concentrations are used in the WQM as mass sinks and sources for the system. The MODSIM water allocation process dynamically includes the ANN-predicted flows. Since these flows are a function of the MODSIM modeled water allocation, the ANN predictions are based on actual system states for the modeled simulation scenario. The WQM is set up to route conservative water constituents from the most upstream points in the system to downstream locations via mass balance calculation on: (1) the ANN-predicted groundwater salt loadings and (2) the ANN-based reservoir salt transport calculation. Figure 5.1 shows a schematic diagram of the conjunctive surface groundwater quantity and quality modeling approach employed in the *River GeoDSS*.

Johnson (1998) remarks that numerical methods are valid and useful when calibrated and used for the same area but have limited capabilities in representing more generalized cause and effect relationships to which they were calibrated. Numerical methods are highly dependent of the system configuration and boundary conditions, since these characteristics are "hard-wired" into the problem and therefore the results. It is well known that ANNs, despite their powerful pattern recognition capabilities, are essentially a sophisticated regression model which treats the physical mechanisms governing the natural system as a "black-box." Such a model is therefore incapable of, or poorly suited to, extension to cases other than those for which it was trained (Suen and Eheart 2003). ANNs have been developed with normalized explanatory variables to perform predictions from explanatory variables spaces that are not training-area specific. For example, the relative elevation of the land in the first area-buffer with respect to the average elevation of the main stream is in a variable space that can be found in different grouping areas without being specific to the training region. The predictions normalized per unit length or unit area of a stream create a similar effect in which the predicted values are applicable to other areas of different size and shapes from the training areas. In conclusion, it is believed that the ANN model design allows discovery of relationships between normalized explanatory variables and normalized outputs than can be applied in other areas in the basin without necessarily extending the training cases.

The ANN used in the *River GeoDSS* for stream-aquifer interaction modeling is trained on a numerically modeled area to recognize patterns between system state changes (i.e., stresses) in the surrounding areas and responses at the modeled interface. The extracted relationships are applied to predict interactions at the interface in both the modeled and neighboring non-modeled areas. The ANN becomes a powerful predictor since it indirectly captures all aspects modeled in the finite difference groundwater model, including detailed non-saturated zone flow and salinity modeling. In this sense, the method does not require inflexible constraints/assumptions and lumped and/or poorly evaluated parameters found in many of the simplified basin scale return flow prediction methods. Since, the ANN is trained based on historical combination of stresses; (i.e., weekly pumping, combined seepage and recharge combined, and calibrated stream-aquifer responses), the system states used for the ANN are realistic and physically based.

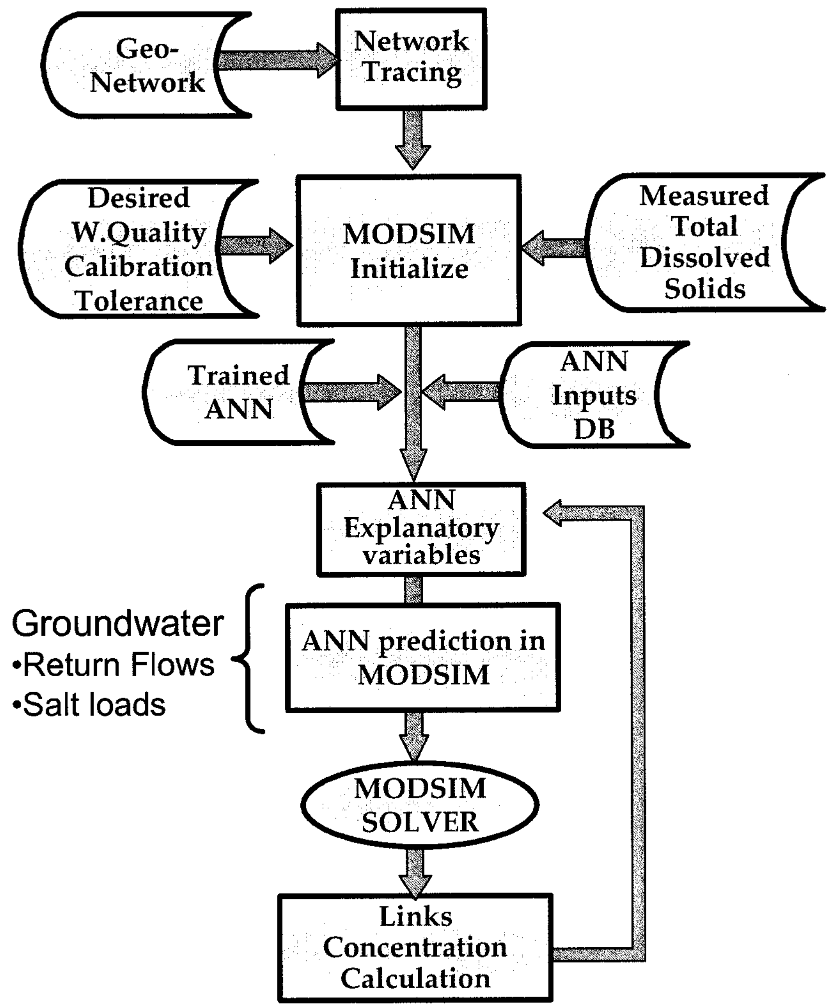


Figure 5.1 – *River GeoDSS* conjunctive quantity and quality modeling diagram

HYDROLOGIC CALIBRATION TOOLS

The *River GeoDSS* features a set of tools for both experienced and inexperienced users to carry out conjunctive surface and groundwater river basin modeling using Geo-MODSIM as the modeling framework. This section describes the types of networks used to calibrate and simulate the network. Appendix III – *MODSIM Network Execution Pre-processing* provides details of internal network manipulation for automating calibration and simulation.

Network Calibration

The *River GeoDSS* provides the tools to construct a Geo-MODSIM calibration network that is capable of quantifying for any network the local gains and losses required to match measured flows at the stream gauging stations. Local gains and losses represent unmeasured flows in/out of the system, such as unmeasured tributary flows, surface runoff from precipitation and irrigation; evaporation, subsurface irrigation return flows, drainage from irrigated fields, and seepage. The local gains and losses also account for measurement errors at gauging stations and points of diversion. The Geo-MODSIM active gauging stations, i.e., stations with available measured flow for the simulated period, are used to create calibration reaches in the modeled basin. Calibration reaches are defined as sections of the river/stream where water is measured at upstream and downstream ends, with each reach composed of all nodes and links traced upstream from a gauging station until other gauging stations are found (on tributaries or the main stem).

Figure 5.2 shows the schema of a calibration reach structure in a MODSIM flow network. The structure contains a source/sink construct connected to all the gauging stations, where excess flow upstream of the station is removed and flow deficiencies at the gauging station are augmented as local gains to the downstream reach. The source and sink nodes are connected by a link that is assigned a negative cost to encourage direct flow from the source to the sink, thereby assuring that only flows required to match the gauged flows are included. The stations are modeled as *flow-through* demands with the measured flows provided as the *flow-through* demand time series, with the immediate downstream link closed. A special case that is implemented when the gauging station lacks measured data sets the time series to zero, thereby preventing flow through the node. In this situation, the algorithm opens the closed-downstream link to allow flow from the upstream reach, where calibration is performed at the next measured downstream gauging station.

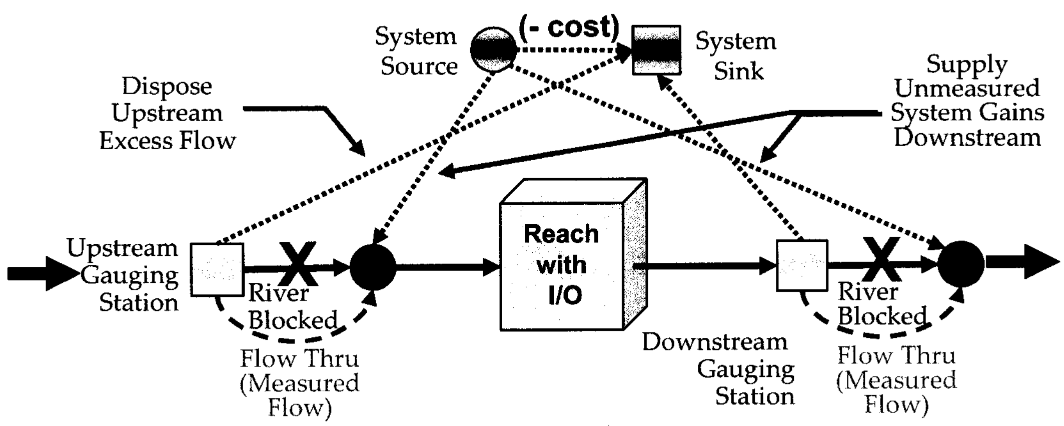


Figure 5.2 – Schematics of the calibration structure for a reach in Geo-MODSIM

During calibration, water is allocated according to MODSIM model settings (i.e., costs and priorities), but only within each reach, since the calibration reaches are isolated from each other. The calibration run is set to completely satisfy the water user demand (usually historical measured diversions) and meet reservoir storage targets, since local unmeasured gains and losses are provided using the system source/sink construct as shown in Figure 5.2. During calibration, water shortages can occur when there are inconsistencies between the measured diversion and the water right entitlements, including the storage water contracts.

A special calibration structure is implemented for the most upstream gauging stations (Figure 5.3) that avoids having water shortages at the most upstream stations by providing a source link to the *flow-through* demand node. A small positive cost is assigned to the link providing local gains to encourage flow through the gauging station. In this case, no excesses are expected upstream of the station, so the link from the most upstream station to the system sink is not implemented.

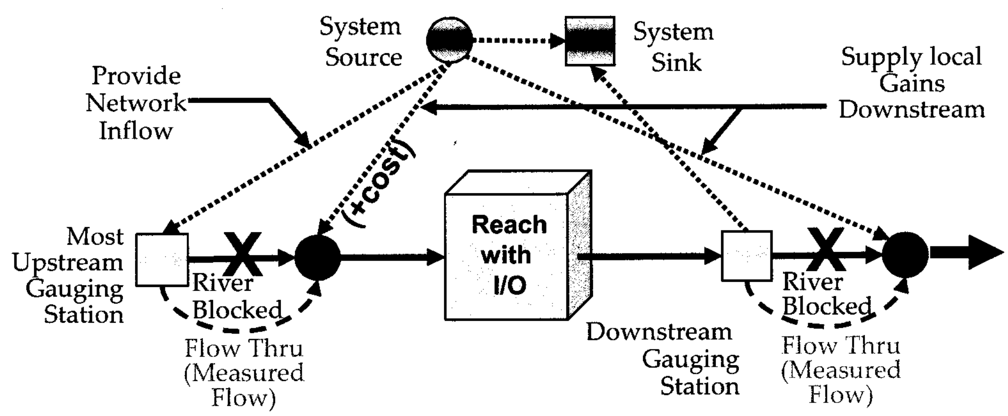


Figure 5.3 – Schematics for the most upstream reach calibration structure

The calibration mode is activated for the active scenario in the *River GeoDSS Model* tab (Figure 5.4).

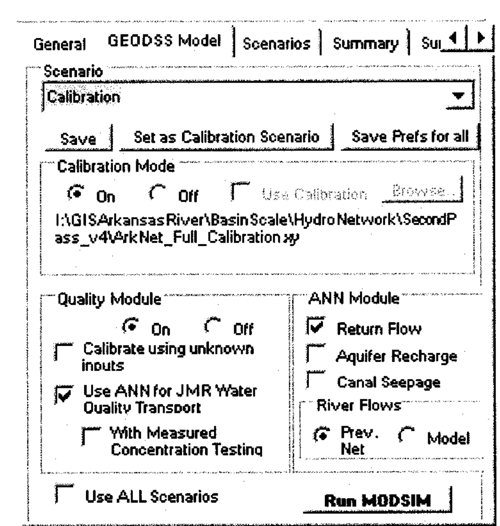


Figure 5.4 – *River GeoDSS* modeling preferences user interface (calibration mode)

Stream-Aquifer interaction modeling in calibration

The ANN-based stream-aquifer interaction modeling can be included in the calibration procedure (using the options in Figure 5.4). In this case, the ANN modeling structures are created and the predicted interaction is represented as additional inflows and outflows at the system nodes. The water allocation process and quantification of local gains and losses, in each reach includes groundwater return flows and depletions. When the stream-aquifer interaction is active, the calibration structures quantify the local gains and losses by excluding the aquifer stream interaction and providing only the additional water needed to remove the excess. Errors (i.e., over/under predictions) in the ANN stream-aquifer predicted flow values are balanced out in the *River GeoDSS* model calibration by removing excesses and adding additional required water.

Semi-automatic Water Quality Calibration Tool

Differences between the measured and modeled concentrations at the control points provide a measure of the magnitude of the correction required (e.g., upstream unmeasured water quality constituent load contributions) during model calibration. At the control points, concentrations can be lowered by adding water of lower concentrations and can be increased by adding more saline water to the reach. The *River GeoDSS* features a water quality semi-automatic calibration tool, which uses the WQM mass routing algorithm (including the ANN reservoir salt transport model) to model concentrations and calculates the modeled concentration deviation from the measured values at the gauging stations. The calibration procedure adjusts the unknown water concentrations in the system (i.e., sources of water with unmeasured water quality) to match as closely as possible the measured concentrations. The water quality calibration process has a large degree of freedom, but is kept realistic using node-based user-controlled concentration ranges. Water quality calibration is triggered in the *River GeoDSS* by checking the box *Calibrate Using Unknown Inputs* (Figure 5.4). When not used during model calibration, the WQM provides water constituent routing using available concentrations, while assuming zero concentrations for the unknown concentrations. Details on the water quality calibration procedure are located in Appendix IV – *Implementation of the Water Quality Calibration.*

The calibration tool accommodates groundwater contributions as predicted by the ANN module by providing salt loads at the system sources (i.e., the most upstream measured stations) that result in computed and measured concentrations agreeing. At system sources with upstream aquifer contributions, which are common on tributaries with gauging stations, the calibration procedure assigns a concentration value to the source link that results in the baseline measured concentration downstream of the station and retains the baseflow as predicted by the ANN. The source link concentrations are not changed during the management scenario simulations, but groundwater contributions can change, thereby affecting contributions from the tributaries (baseflow) during the simulation scenarios.

Simulation Networks

Two simulation modes are available in the *River GeoDSS.* The first is the standard MODSIM run, in which water is allocated using the included time series and network flow preferences. In this case, the *River GeoDSS* calibration structures are not created, making the user responsible for providing the inflow time series and calibration flows. The second mode performs river basin simulation that automatically includes the calibration results for add/remove of calculated local gains and losses (options in Figure 5.5). This feature is particularly useful for simulating "what if" management alternatives. The gains and losses computed during calibration are volumes that, according to the measured data, should have been present in the system to achieve mass balance. For the simulation mode, the flows are incorporated as fixed system inputs and outputs. This operation assumes that for management alternative simulation, the historical conditions that generated the gains and loses are replicated. In some cases, this assumption may introduce errors in the simulation. For example, if the management alternative includes significant changes in irrigation practices, flows at the ends of the canals, and/or the irrigation runoff, may differ from that portion computed in the calibration flows. The simulation of management scenarios using the baseline calibration flows allows comparison of alternatives using the baseline conditions as the default structure. Errors generated from changes in local gains and losses during implementation of the management alternatives are expected to be negligible since the major changes in system flows are accounted for in the simulation.

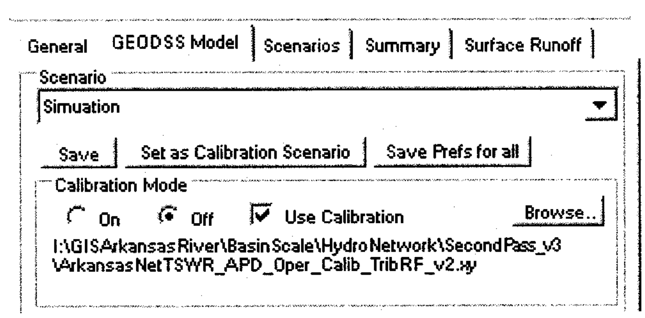


Figure 5.5 – User interface for selecting simulation mode using calibration results

During simulation, the calibration structures are created and adapted to allow modeling of the calibration inflow/outflows and simulate uninterrupted flow through the gauging stations by opening their downstream link, thereby allowing the basin-wide priorities and costs to dictate water allocation. Gauging stations are modeled as low priority *flow-through* demands, with the time series of calibration link upper bounds set to the computed flows from the calibration run. Figure 5.6 shows a diagram with the elements of the calibration structure in the simulation network.

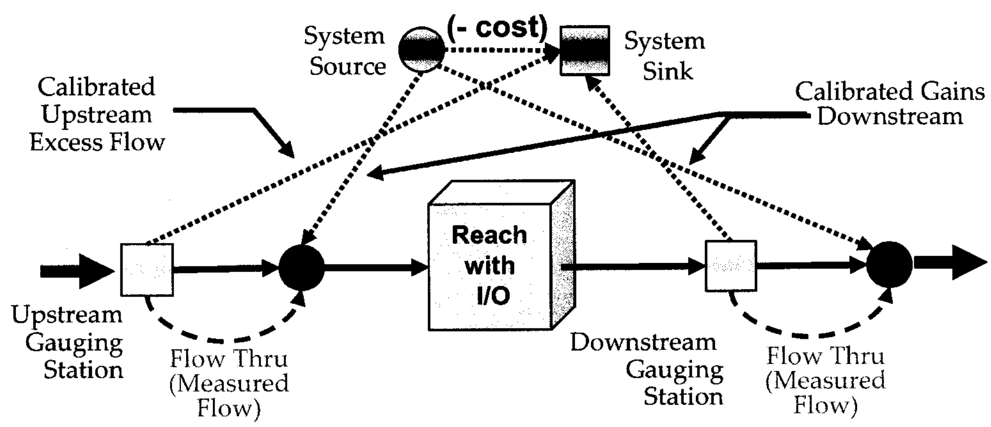


Figure 5.6 – Schematics of a calibration structure in simulation

Stream-Aquifer interaction modeling in simulation

As in calibration, the ANN module can be used in simulation to represent the stream-aquifer interaction. For each simulation, the ANN module builds the simulation dataset using the simulated management alternative conditions; therefore, the predicted return flow/depletions dynamically account for changes in the system conditions.

Water Quality Simulation

In the simulation run, concentrations calculated during the water quality calibration are assigned to the corresponding points. At each time step, the *River GeoDSS* uses the concentrations stored in the calibration network output file to set them as sources in the network. With all concentrations assigned, the WQM performs salinity routing continuously from the most upstream nodes to the system sink at most downstream end.

Approach and Application Discussion

The *River GeoDSS* methodology to model basin scale stream-aquifer interaction is a powerful alternative to traditional methods without requiring restrictive simplifications, extensive data requirements and cumbersome calibrations. The method employed in the *River GeoDSS* requires fewer resources and data than directly using basin scale distributed parameter models (e.g., MODRSP, MODFLOW or IGSM2), which are computationally intensive and require an extensive/expensive hydro-geologic data base, basin-wide monitoring, and intricate model calibration. Aquifer response coefficients derived at several points in the system using MODRSP (Maddock and Lacher 1991), or a vector-based approximation as in AQUATOOL, in which the eigenvector technique is used to represent the aquifer response (Andreu and Sahuquillo 1987), are methods better suited for a basin scale application when linearity assumption are acceptable. However, relying on a comprehensive underlying groundwater model (usually a distributed model), these methods can become impractical as well.

The conjunctive use modeling approach presented herein is applied in the *LAR GeoDSS*. In this study area, the previously developed SDF coefficients (Jenkins et al. 1972) are considered to be limited. The aquifer simplifications inherited from the Glover (1974) equations that use monthly time steps the SDF approach, and the simplified stream-aquifer model used in Jenkins study, are restrictive for accurately evaluating management alternatives in the basin. On the other hand, the current regional-scale groundwater model for the area (Burkhalter and Gates 2005, Burkhalter and Gates 2006), calibrated with extensive field data and including comprehensive salt modeling in the saturated and unsaturated zones for salinity remediation alternatives evaluation, perfectly suits the *River*

GeoDSS methodology, providing a useful resource to evaluate salinity management alternatives at basin scale.

Integration of the *River GeoDSS* components in both calibration and simulation allows state-of-the-art conjunctive groundwater and surface water quantity and quality modeling. The *River GeoDSS* modeling tools greatly simplify the calibration-simulation process, facilitating the evaluation of "what if" management scenarios. The dynamic usage of pre-calculated local gains and losses directly from the MODSIM output files, in conjunction with the simulation scenario manager, reduces the chances of large data management errors and expedites the simulation of management alternatives, and therefore, the decision making process.

CHAPTER 6

RIVER GEODSS FRAMEWORK FOR THE LOWER ARKANSAS RIVER VALLEY, COLORADO

Described herein is the construction and application of the *River GeoDSS* framework to the LARV as a customized version for handling basin-specific data and characteristics, and problem-specific analysis. The *River GeoDSS* implements the full functionality of the spatial decision support system, including MODSIM tools for administrative and institutional water allocation modeling, such as water rights, the Arkansas River compact, storage water contracts and alternate points of diversion, coupled with *River GeoDSS* modules for conjunctive use water quantity and quality modeling. The objective of this *River GeoDSS* development is to build a tool to analyze the feasibility and effects of the regionally-defined water management alternatives in a heavily legal and administrative constrained system. The topics discussed in this chapter include: (a) gathering the data, (b) creating the geo-network, (c) describing the set of custom tools developed for *River GeoDSS* application in this basin, and (d) calibrating and simulating the system.

SPATIAL-TEMPORAL DATABASE

A comprehensive spatial-temporal database was developed for the LARV to support modeling, analysis and decision making tasks. The database is assembled with information from the USGS, Army Corps of Engineers, the CDWR, the NRCS and CSU field-collected and digitized data. Spatial data are compiled in ESRI® geo-databases; while, temporal data are stored in native MS-Access database format. Spatial data in the GIS platform facilitates integration and cooperation between research studies at the field, regional and basin scales. The database includes digital topography, political divisions, hydrography, hydraulic structures (e.g., canals, dams, siphons, and diversion structures), irrigated fields, Soil Survey Geographic Database (SSURGO), land use types, bed rock scatter points, aerial photos (DOQs), satellite images and spatially referenced field data. Diversion structures and reservoirs have associated water rights which are relationally joined with the GIS features. Dynamic features include measurements or characteristics varying in time, including water quantity and quality measurements in both surface and groundwater systems, climatic variables, water diversions, and groundwater pumping. Measurements are stored in database tables and relationally joined with spatially-referenced features such as gauging stations, climatic stations, diversion structures, pumping wells, and monitoring wells. NOAA–NEXRAD precipitation data are processed into raster maps and made available for the *River GeoDSS*. The database also contains processed data such as watersheds, slopes, hydrologic networks, geometric networks, and geo-referenced groundwater model results. Samples and details of the spatial-temporal database are found in Appendix V – *Spatial-Temporal Database Description.*

GEOMETRIC NETWORK

The geometric network for the *LAR GeoDSS* is based on the USGS NHD network. The network elements are filtered, processed and imported into the *LAR GeoDSS* data-model, with stream detail reduced to the major tributaries and the Arkansas River. The study region extends from Pueblo Reservoir to the Colorado-Kansas state line. Flow directions are assigned using the digitized direction, which works well for natural streams, but needs to be manually edited for canals and drains in the system. The network flow direction and connectivity rules are implemented to accurately represent the physical system water movement. Complementing information from aerial photography, a system field reconnaissance was performed in 2005 providing ground truthing for the geometric network flow and connectivity implementation. The reconnaissance visited more than 250 locations in the study area to observe hydraulic characteristics. Photographs of the visited points and observations are digitally available in the *LAR GeoDSS* database (see Appendix V – *Spatial-Temporal Database Description* for an example). The ESRI Utility Network Analyst extension was used to check connectivity of nodes and links, perform network traces and verify flow paths. Figure 6.1 shows an example of the geometric network in ArcMap, including flow directions (blue arrows) and a Utility Net Analyst downstream trace result (in red) from the XY canal diversion. These traces allow the checking of water quality mixing of flows at the canal-tributary intersections.

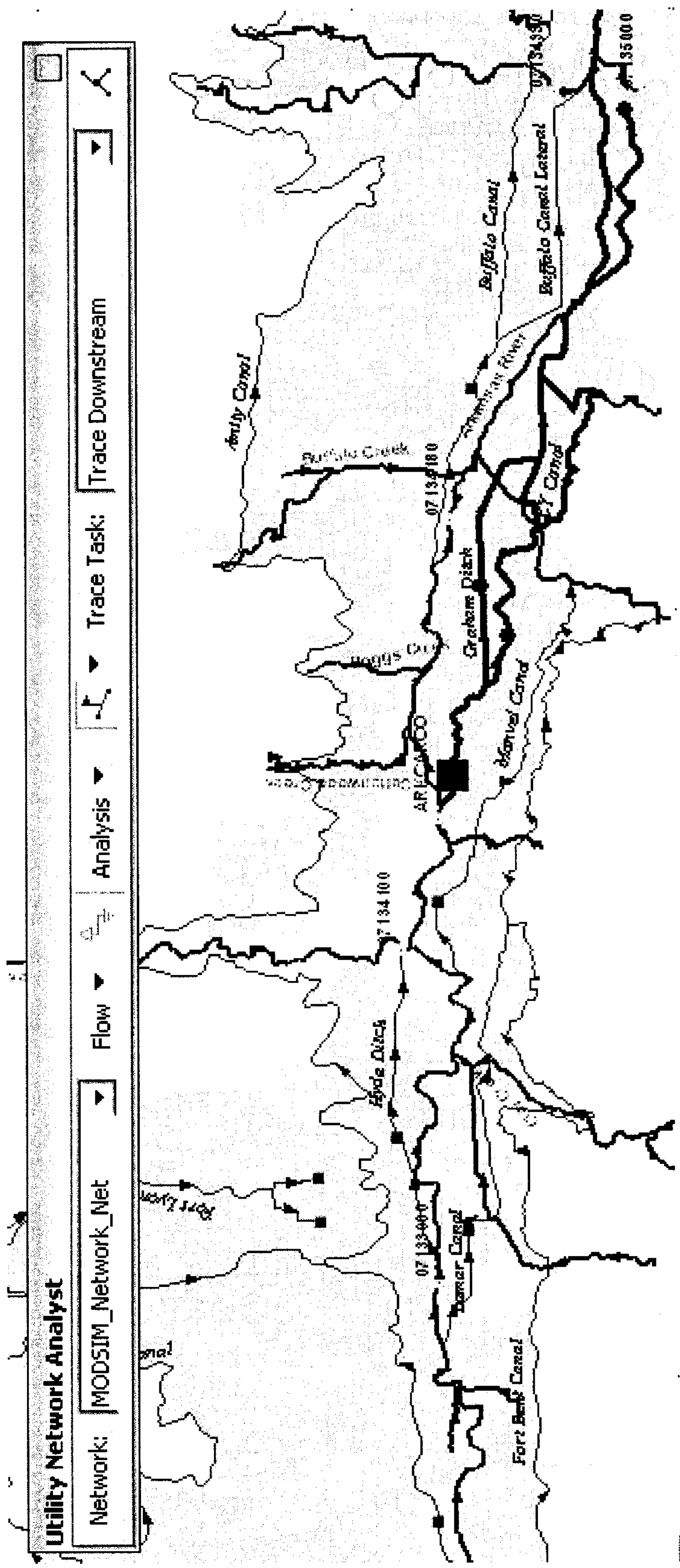


Figure 6.1 – Geometric network sample in ArcMap

GEO-MODSIM NETWORK

The Geo-MODSIM Base-Network for the *LAR GeoDSS* was generated from the geometric network. Reservoir capacities and node priorities were imported from the data-model and stored with the MODSIM Base-Network. Pueblo Reservoir and John Martin Reservoir were assigned priorities of 500 and 600, respectively, which give initial preference to water storage upstream. Gauging station demand nodes were assigned the default priority of 100, with consumptive demand nodes assigned a priority of 500. This priority scheme allows water rights to be assigned cost rankings from 0 to -5000, with a MODSIM aggregated cost of the water right link and the demand node artificial link ranging from -45000 to -50000. The demand priorities are set and saved in the data-model *MOD_Cost* field. Links were assigned the default zero cost values, except for the link connecting the Holbrook Canal diversion back to the main river and reservoir bypass links which were assigned with a positive cost of 10 to discourage use of these routes. Figure 6.2 shows the selected (bright blue) return link from the Holbrook Canal diversion that is assigned a positive cost.

The *LAR GeoDSS* employs special structures to model irrigation canal diversions as consumptive demands. The consumptive demands located close to the diversion point were modeled as *flow-through* demands with water right links immediately downstream of the node pulling water into the canal system but allowing diverted water to continue flowing to the end of the canal where it is "consumed" by the terminal interface. Flowing diverted water through the canal links allows querying and display of diverted flow anywhere in the canal, especially useful for analysis of long canals that extend for dozens of kilometers. If applicable, the terminal interface allows the return of a fraction of the diverted flow back to the river system.

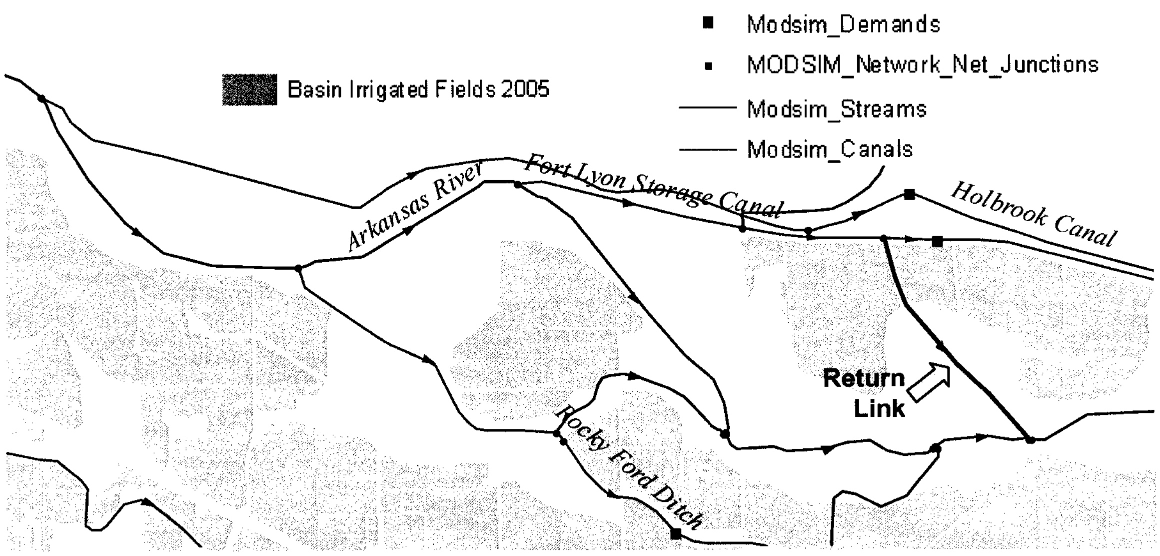


Figure 6.2 – Diversion return link example

Data obtained from Abbott et al. (1985) were used to populate the reservoir capacities in the data-model. These values were stored in the geo-database and transferred to the Geo-MODSIM network using the *River GeoDSS* interface menu item *Tools → Load data-model Data*.

CUSTOMIZED *RIVER GEODSS*

This section describes the set of customized *River GeoDSS* tools for the LARV modeling. An enhanced *River GeoDSS* interface was implemented to provide access to the custom data management and analysis tools. The custom tools include importing time series data, water rights data, and system characteristics, as well as managing and analyzing "what if" water management scenarios, and handling storage water operations and alternate points of diversion. The tools are presented in two groups, where the first group includes tools for system model assembly, and the second group consists of tools designed to handle customized analysis.

System Model Assembly

This section describes tools that are used to build and populate the *LAR GeoDSS* modeling system. Theses tools are developed to handle particular data formats, units and specific characteristics of the Arkansas River basin. Description of the underlying analysis and assumptions is also provided in this section as a reference for the appropriate utilization of these tools. Time series data in the *LAR GeoDSS* were compiled into a central database, with detail on the file structure provided in Appendix V – *Time Series Database*. The time series database is accessed by the tools described in this section, with the database location defined in the *Data Management* Interface.

Reservoir Storage System

The LARV contains two on-stream reservoirs (Pueblo Reservoir and John Martin Reservoir), and nine major off-stream reservoirs for irrigation purposes. Based on the system operation described in Abbott et al. (1985), several reservoir storage processes occur in the basin. Lake Henry and Lake Meredith, off-stream reservoirs owned by the Colorado Canal, are used to store water during the winter. The location of Lake Meredith, however, requires an exchange with the Holbrook Canal, the Fort Lyon Storage Canal, or the Arkansas River for the Colorado Canal irrigators to use the stored water. Although limited availability of historical records requires disabling these reservoirs in the *LAR GeoDSS*, exchanges in the records are modeled as storage water diversions (see "Storage Diversion and Exchanges").

The Great Plains Reservoirs [Nee So Pah (Black River), Nee No She (Standing Water), Nee Gronda (Big Water), and Nee Skah (Queens) reservoirs] are part of the Amity Canal system. These reservoirs are broad shallow lakes where the surface-area-to-capacity ratio produces significant evaporation losses. Since a large dead-storage pool permits more stored water than can be withdrawn, storage for the Amity Canal is maintained in John Martin Reservoir whenever possible. Since no records are found for diversion from these reservoirs, they were disabled in the current version of the *LAR GeoDSS*.

The Holbrook Canal can store water in Holbrook Reservoir, but this reservoir is unable to deliver water to the irrigated lands and requires an exchange with the river to use stored water. Diversion records for Holbrook Reservoir are only available for dates prior to 1983, thereby limiting the modeling of storage in this reservoir. Storage water records were used to model water exchanges.

The Fort Lyon Storage Canal delivers water to Horse Creek Reservoir and Adobe Creek Reservoir, with the ability of releasing irrigation water directly to the Fort Lyon Canal. Since these reservoirs have negligible impact on the entire system operation and because of the lack of readily available data, therefore they were disabled in the *LAR GeoDSS*.

Flow Data

Flow data at gauging stations in the Arkansas River Valley are available from the USGS and CDWR. The raw daily data were stored in the time series database, where the current database includes USGS data ranging from 1912 to September 2004 and CDWR data from 1935 to December 2003 for a total of 24 stations in the river basin. Table 6.1 and 6.2 provide a summary of the active gauging stations available in the database as well as their periods of record and average flow.

Table 6.1 – CDWR Gauging Stations Summary

Name	HydroCode	DataFrom	DataTo	Values Count	Average (cfs)
ARKANSAS RIVER NEAR CARLTON @ X-Y DITCH DAM	ARKCARCO	10/1/1999	9/30/2003	2557	175.12
ARKANSAS RIVER NEAR NEPESTA	ARKNEPCO	10/1/1935	9/30/2003	26571	672.52
ARKANSAS RIVER NEAR ROCKY FORD	ARKROCCO	10/1/1999	9/30/2003	2557	270.15
CROOKED ARROYO NEAR SWINK	CANSWKCO	2/1/1968	9/30/2003	13957	12.05
HORSE CREEK AT HIGHWAY 194	HRC194CO	10/1/1979	9/8/2003	8232	17.17
PURGATOIRE RIVER AT NINEMILE DAM, NEAR HIGBEE (C	PURNICCO	1/1/1998	9/25/2003	2019	71.28
PURGATOIRE RIVER BLW HIGHLAND DAM NR LAS ANIMAS	PURHILCO	5/23/2001	9/22/2003	643	28.49
ARKANSAS RIVER AND CATLIN CANAL (COMBINED)	ARKCACCO	1/1/1998	9/30/2003	2098	657.45

Table 6.2 - USGS Gauging Stations Summary

Name	HydroCode	DataFrom	DataTo	Values Count	Average (cfs)
APISHAPA RIVER NEAR FOWLER	07119500	4/1/1922	9/30/2004	25511	20.48
ARKANSAS RIVER ABOVE PUEBLO	07099400	10/1/1965	9/30/2004	14610	602.41
ARKANSAS RIVER AT LA JUNTA	07123000	4/1/1912	9/30/2003	33778	240.33
ARKANSAS RIVER AT LAMAR	07133000	6/1/1913	9/30/2004	32385	183.10
ARKANSAS RIVER AT LAS ANIMAS	07124000	6/1/1939	9/30/2004	24229	236.37
ARKANSAS RIVER AT MOFFAT STREET AT PUEBLO	07099970	10/1/1988	9/30/2004	6209	565.81
ARKANSAS RIVER BELOW JOHN MARTIN RESERVOIR	07130500	4/1/1938	9/30/2004	24443	332.65
ARKANSAS RIVER NEAR AVONDALE	07109500	5/1/1939	9/30/2004	19388	848.00
ARKANSAS RIVER NEAR GRANADA	07134180	12/5/1980	9/30/2004	9066	213.97
BIG SANDY CREEK NEAR LAMAR	07134100	2/1/1968	9/30/2004	8951	18.25
FOUNTAIN CREEK AT PUEBLO	07106500	1/1/1922	9/30/2004	23022	137.46
FOUNTAIN CREEK NEAR PINON	07106300	4/1/1973	9/30/2004	11221	154.75
HUERFANO RIVER NEAR BOONE	07116500	1/1/1922	9/30/2004	8712	43.44
PURGATOIRE RIVER NEAR LAS ANIMAS	07128500	1/1/1922	9/30/2004	24406	79.21
SAINT CHARLES RIVER AT VINELAND	07108900	10/1/1978	9/30/2004	9862	39.93
TIMPAS CREEK AT MOUTH NEAR SWINK, CO.	07121500	1/1/1922	9/30/2004	15097	58.18
TWO BUTTE CREEK NEAR HOLLY, CO.	07135000	6/9/1942	8/3/1999	59	39.31
ARKANSAS RIVER NEAR COOLIDGE, KS	07137500	1/1/1998	9/30/2003	2099	345.30
CHICO CREEK NEAR PUEBLO CHEMICAL DEPOT	07110400	1/1/1998	9/30/1999	612	7.35
WILD HORSE CREEK ABOVE HOLLY	07134990	3/18/1998	9/30/2004	1612	20.89

Diversion records for all water users in the basin are maintained and provided by the CDWR, with daily diversion records included in the *LAR GeoDSS* time series database. The records include flags and user id to track regular diversions as well as storage water and alternate points of diversion. The database includes more than 300 water users with water use records ranging over the period 1910 to 2004.

Reservoir storage data are maintained by the US Army Corps of Engineers, Albuquerque District, and the USBR. The USBR makes available the Pueblo Reservoir daily data through the *HydroMet* database, and storage levels from 1999 to 2005 were stored in the *LAR GeoDSS* time series database. John Martin Reservoir data were downloaded from the US Army Corps of Engineers web page and complemented with data from 1970 to 1991 as provided by the Albuquerque District personnel.

Gauging Stations

Flow data at the gauging stations represent inputs or check points along the system. The most upstream gauging stations in the network were used as network sources, with intermediate stations used in calibration to quantify local gains and losses. The measured flows were loaded into the corresponding demand node time series, where the system source nodes, modeled as *flow-through* demand nodes, request the measured flow from the calibration structure and convey the flow downstream. Intermediate control points regulate the automatic calibration of the network and can be used for comparison of simulated flows with the baseline network during simulation of the management alternatives.

Diversion Water

Historical diversion records were used to populate the water demand time series data sets according to the modeled time step. Daily values were extracted, using the CDWR Water Bank Codes (described in Appendix V). In this application, these daily flows were then summed to weekly volumes for modeling purposes.

The diversion data for certain water users required special handling since these users were under a different water district subsequent to water year 1999 (Table 6.3). This situation is identified by users having the same structure ID and user name under different water district (WD) numbers. Diversion records for these users associated with WD 14 extend through water year 1999, and then are associated with water district 17 thereafter. CDWR personnel expressed that in this situation, where both water districts have records and the data are expected to be duplicated, data for only one of the water districts is required for processing in the *LAR GeoDSS*.

Table 6.3 – Three Digit Structures with Data under Different WD Numbers

ID	WD Nos.	NAME
540	14, 17	COLORADO CANAL
542	14, 17	ROCKY FORD HIGHLINE
558	14, 17	ROCKY FORD DITCH
652	14, 17	LAS ANIMAS TOWN DITCH
659	14, 17	COLO CANAL RETURN FLOWS

Reservoir Storage Data

Even though all major reservoirs in NHD dataset were included in the geometric network, only the on-stream Pueblo and John Martin Reservoirs in the LARV have readily available measurements of historical daily volumes, inflows and outflows to populate storage target time series and be modeled as standard MODSIM reservoir. Off-stream reservoirs were modeled based on the storage water diversion records as discussed subsequently under "Storage Water Diversion and Exchanges". For calibration purposes, reservoir storage targets were set to the historical measured volumes in the reservoirs. For simulation of management alternatives, two reservoir modeling modes were tested: (1) historical storage was used as the target storage level and (2) reservoir layers were used to balance the system storage between the active reservoirs (described in detail in Chapter 7 – *Reservoir Operational modes*).

Time Series Import Tool

The *LAR GeoDSS Time Series Import* tool processes the daily flows stored in the database according to the modeled time step and units. The tool imports: (1) the processed gauging station flow data into the corresponding *flow-through* demand nodes that represent the gauging stations, (2) measured diversions into the corresponding consumptive use demands, and (3) historical reservoir storage levels as reservoir targets and reservoir initial volumes for the corresponding simulation start date.

The tool is accessed as a menu item in: *Arkansas Tools→Populate Time Series→All Historical.* The tool allows importing time series for all existing nodes in the network or for a selected node from a list. A zero value is used to fill missing daily data, indicating no flow contributions for these time steps.

The reservoir initial volume entries are populated with the historical reservoir volumes at the beginning of the simulation period, and the target volumes are assigned as historical storage levels at the end of each time step.

Precipitation Data

Spatial precipitation data were processed into the *LAR GeoDSS* using raster maps generated by two methods: (1) NEXRAD Stage III data and (2) spatially interpolated climate station measurements.

NEXRAD Stage III employs operational hourly rain gauge data, and interactive quality control by Hydrometeorological Analysis and Service (HAS) forecasters at the National Weather Service River Forecast Centers to produce the Digital Precipitation Array (DPA) products. DPA products are generated by the Precipitation Processing Subsystem (PPS), which is one of many automatic algorithms in the WSR-88D Radar Product Generator (Fulton et al. 1998). Radar-based NEXRAD Stage III spatial precipitation data were collected from National Oceanic and Atmospheric Administration (NOAA) Hydrologic Data Systems for the LARV from 1997 to 2005. The downloaded hourly data were processed and compiled into daily raster maps using a *River GeoDSS* utility for accumulating precipitation according to the modeled time steps. Figure V-6 (in Appendix V) shows a sample of the resulting weekly-precipitation raster map.

Both the NWS and CoAgMet maintain climate stations that were utilized for this project. Since the climate stations provide point-based precipitation in the Valley, the *River GeoDSS* implements a utility (Figure 6.3) to generate spatial precipitation raster maps from the point-measured values. This utility uses the time series database data and file preferences in the *River GeoDSS Data Management* Interface (Figure 3.3). The station points are assigned the measured values and simple spatial interpolation (using the inverse distance weighting (IDW) method) is performed to generate sets of raster precipitation maps. In addition to simplifying automation, IDW introduces smaller errors on estimates of climatic discontinuous phenomena such as precipitation, than other spatial interpolation methods with smoothing effects (e.g., Kriging) (Brown and Comrie 2002). Figure 6.4 shows an example of the weekly spatial interpolated precipitation and the stations used in the processing.

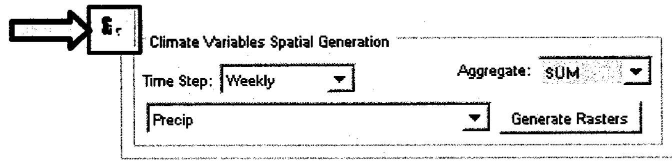


Figure 6.3 – Spatial Climate variables generator utility interface

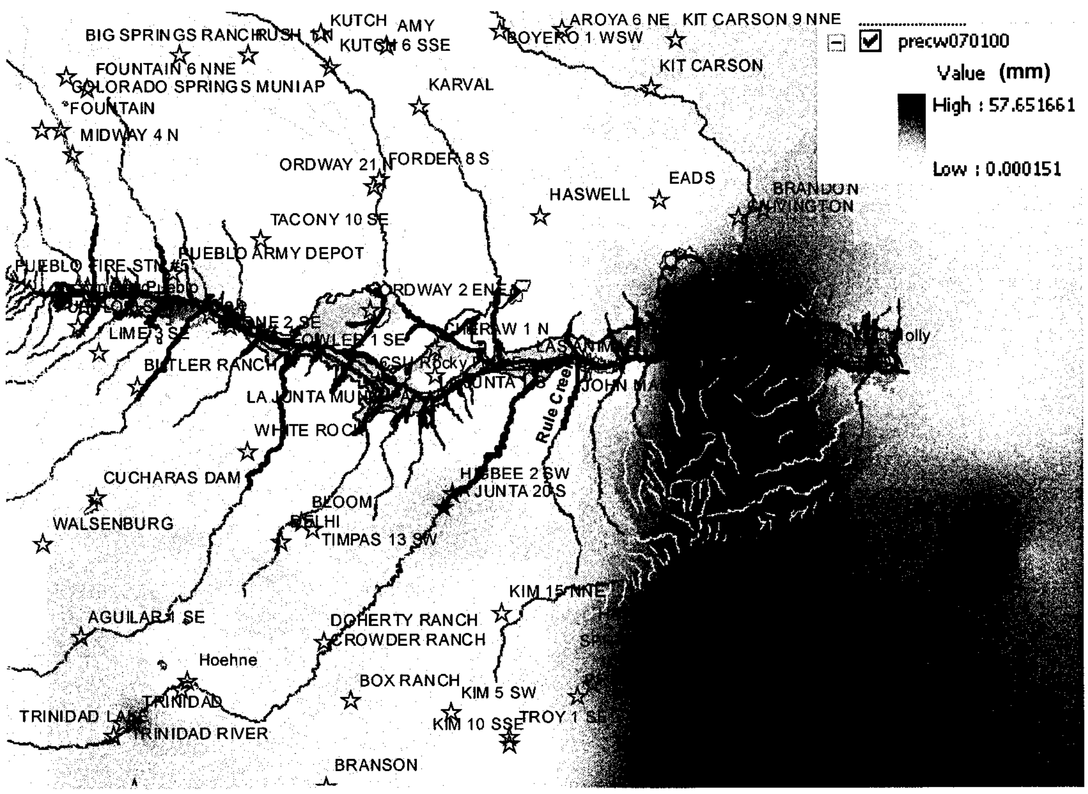


Figure 6.4 – Spatial precipitation interpolated from point-based measurement (location indicated by ☆)

Precipitation summary databases were created using a *LAR GeoDSS* utility (Figure 6.5) that implements the ArcGIS *zonal statistics* function for the user-specified zones. This utility generates tables of precipitation statistics for the specified zones (e.g., polygons, lines or points) for each modeled time step. The utility uses *LAR GeoDSS Data Management* Interface preferences for output database names and locations. Currently, precipitation data are exclusively used as an ANN explanatory variable in the stream-aquifer interaction modeling. For ANN training, the regional-scale groundwater model time steps were used based on 52 weeks per year starting on April 1st. The corresponding weekly precipitation raster maps and summary tables were created starting on April 1st for the modeled years. The *LAR GeoDSS* simulations with the ANN-based stream-aquifer interaction relied on previously-generated precipitation summary tables labeled with the time step starting date. Since MODSIM time steps are continuous and uniform from the model start date, the *LAR GeoDSS* run requires the generation of slightly shifted raster maps and summary tables beginning with the second year of simulation. As a consequence, the precipitation summary database contains tables for both MODFLOW-MT3DMS and MODSIM time step start dates.

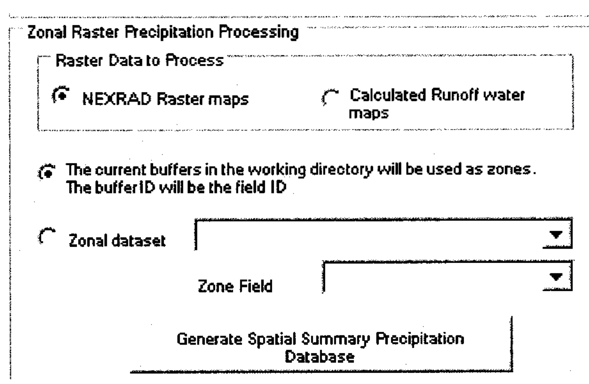


Figure 6.5 – Precipitation summary database generation utility interface

Water Quality Data

A *LAR GeoDSS* water quality database stored measured specific conductance values downloaded from the USGS collected between 1963 and 2005. Specific conductance of the samples were collected in two modes: (1) regular intervals (e.g., 15 min, 30 min), and (2) irregular intervals (i.e., grab samples). The database includes both sample modes using a type id to flag them. Table 6.4 shows a summary of the stations, the type of data collected, the number of samples available, and the earliest and latest sample in the record.

Table 6.4 – Water Quality Measuring Stations Summary

Name	Station ID	Data Type	Data Count	From Date	To Date
APISHAPA RIVER NEAR FOWLER	7119500	Regular	462	11/26/1963	05/07/2003
ARKANSAS RIVER ABOVE PUEBLO	7099400	Irregular	6809	04/01/1986	09/30/2005
ARKANSAS RIVER ABOVE PUEBLO	7099400	Regular	294	10/15/1965	09/28/2005
ARKANSAS RIVER AT LA JUNTA	7123000	Regular	91	10/20/1961	09/12/2005
ARKANSAS RIVER AT LAMAR	7133000	Regular	556	11/27/1963	09/08/2003
ARKANSAS RIVER AT LAS ANIMAS	7124000	Irregular	6422	12/04/1985	09/30/2005
ARKANSAS RIVER AT LAS ANIMAS	7124000	Regular	977	11/06/1945	09/20/2005
ARKANSAS RIVER AT MOFFAT STREET AT PUEBLO	7099970	Irregular	5434	10/05/1988	09/30/2005
ARKANSAS RIVER AT MOFFAT STREET AT PUEBLO	7099970	Regular	119	10/24/1988	09/07/2005
ARKANSAS RIVER BELOW JOHN MARTIN RESERVOIR	7130500	Irregular	6892	12/05/1985	09/30/2005
ARKANSAS RIVER BELOW JOHN MARTIN RESERVOIR	7130500	Regular	1291	10/09/1945	09/20/2005
ARKANSAS RIVER NEAR AVONDALE	7109500	Irregular	7081	07/31/1979	09/30/2005
ARKANSAS RIVER NEAR AVONDALE	7109500	Regular	916	02/04/1969	09/14/2005
ARKANSAS RIVER NEAR COOLIDGE, KS	7137500	Irregular	1896	10/01/1999	09/30/2005
ARKANSAS RIVER NEAR COOLIDGE, KS	7137500	Regular	687	11/27/1963	08/28/2003
ARKANSAS RIVER NEAR GRANADA	7134180	Regular	253	02/21/1919	09/08/2003
BIG SANDY CREEK NEAR LAMAR	7134100	Regular	281	02/07/1968	09/08/2003
CHICO CREEK NEAR PUEBLO CHEMICAL DEPOT	7110400	Regular	44	04/28/1997	01/19/2000
FOUNTAIN CREEK AT PUEBLO	7106500	Regular	700	11/26/1963	09/08/2005
FOUNTAIN CREEK NEAR PINON	7106300	Regular	715	04/17/1973	07/21/2005
HUERFANO RIVER NEAR BOONE	7116500	Regular	311	04/01/1976	06/06/2003
PURGATOIRE RIVER NEAR LAS ANIMAS	7128500	Regular	667	12/20/1961	09/09/2003
SAINT CHARLES RIVER AT VINELAND	7108900	Regular	400	11/05/1971	09/06/2005
TIMPAS CREEK AT MOUTH NEAR SWINK, CO.	7121500	Regular	454	03/14/1967	07/01/2003
TWO BUTTE CREEK NEAR HOLLY, CO.	7135000	Regular	2	08/07/1997	08/13/1997

The *River GeoDSS Water Quality Import* tool (Figure 3.14-B) was used to process and transfer the downloaded data into the network objects, with both regular and irregular data imported (see Appendix III – *River GeoDSS Water Quality Import Tool* for details and data type analysis).

Calibration Concentration Range

Field data collection in the Arkansas River Valley provided information for setting the range of valid concentrations for water quality calibration. The *LAR GeoDSS* implements a utility to guide the selection of this concentration range. The utility uses the database to present the user with maximum and minimum measured values at selected points in the system. The user can also group observed concentration values based on the types of water bodies where the measurements were taken. The types implemented in the database for this purpose are: (1) River, (2) Small Tributary (NHD level 4), (3) Large Tributary (NHD Level 3), (4) Reservoir, (5) Canal, (6) Drain, and (7) Lateral. In addition, the user can query maximum and minimum values imported into the node concentration time series data. Lastly, the user can manually enter the concentration values to be used as upper and lower limits. Figure 6.6 shows the user interface for this utility to guide the setting of calibration concentration limits. This utility can be accessed for a single gauging station (Figure 3.12) or can be used to set default values for all nodes in the system (accessed through the menu item: *Tools→Calibration Concentration→Set Defaults (Min/Max)*).

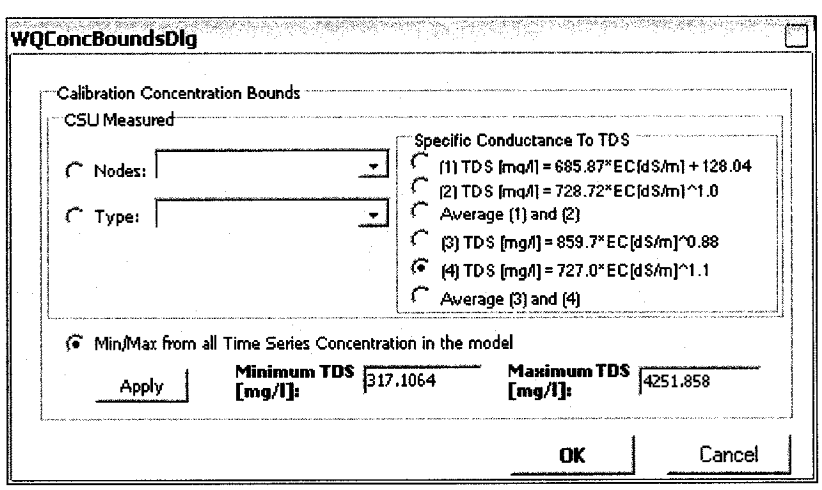


Figure 6.6 – Calibration concentration bounds guide utility interface

Table 6.5 shows a summary of the maximum and minimum values for the USGS measurements and the different types of system objects for the CSU field measurements.

Table 6.5 – Measured Concentration Limits by Measured Water Body Type

Measured Object Type	Minimum TDS [mg/L]	Maximum TDS [mg/L]
Canal	172.90	3272.50
Drain	250.78	1143.955
Large Tributary (Level 3)	477.19	2035.77
Lateral	283.63	904.75
Reservoir	280.55	975.97
River	223.69	4072.89
Small Tributary (Level 4)	307.65	2748.42
USGS Measured Time Series	317.10	4251.86

In this case study, the allowable concentration range for calibration of unmeasured flows was set basin-wide between 0 and 4500 mg/L to provide flexibility for diluting or concentrating water in the reach according to the downstream measurements. This concentration adjustment includes compensation for groundwater return flow over/under predictions.

Concentration and Flow Relationship

Cain et al. (1987) developed log-log streamflow-specific conductance equations for the Arkansas River basin, Colorado, such as log specific conductance predicted as a function of log streamflow. The same equation form was used for all stations, and accommodates bi-seasonal relationships from May through September and from October to April. The relations developed for 19 Arkansas River and 50 tributary stations explain between 12 and 88 percent of the variation in the data. A regionalization approach was used to estimate the bi-seasonal equation coefficients for stations with insufficient data for estimating the coefficients. In this case, coefficients were estimated using regression equations of the drainage area, mean annual precipitation at the station, percent of the drainage area that is irrigated, and percent of the drainage area that is underlain by shale bedrock.

In the *LAR GeoDSS*, concentrations were computed for stations with irregular measured concentration as a function of the measured flow using a fitted regression equation individually developed for each station. These regression equations allow concentration to be predicted as a function of time step flow for filling periods that lack measured concentrations. During simulation, the flow-concentration relationships were used for all time steps, regardless of the measurement availability. The regression equations generate changes in concentration due to changes in flow during the modeling of management alternatives. Appendix V contains details on the basic flow-concentration relationships developed for the *LAR GeoDSS* to estimate concentrations at stations with missing data. Table 6.6 summarizes the regression equations and station information for the irregular measured stations.

Table 6.6 – Regression Equation Summary of Irregular Sampling Stations

Station Name	MODSIM Name	Period Available	Samples Available	Regression Equation (x= weekly Flow [Acre-ft])	r^2
SAINT CHARLES RIVER AT VINELAND	STCHARCO	1978 – 2004		Conc=(3384.86)+(-345.28)*log(x)	0.69
HUERFANO RIVER NEAR BOONE	HUEBOCO	1979 – 2003	264	Conc=(4431.61)+(-417.77)*log(x)	0.70
APISHAPA RIVER NEAR FOWLER	APIFOWCO	1963 – 2003		Conc=(5360.23)*x^(-0.26942)	0.80
CHICO CREEK NEAR PUEBLO CHEMICAL DEPOT *	CHICRECO	1997 – 2000		Conc=exp((-.00267)*x+(7.11166))	0.66
TIMPAS CREEK AT MOUTH NEAR SWINK,CO	TIMSWICO	1967 – 2003		Conc=(10757.5)*x^(-0.30695)	0.82
ARKANSAS RIVER AT LA JUNTA *	ARKLAJCO	1961 – 2002	73	Conc=(3455.02)+(-285.51)*log(x)	0.88
PURGATOIRE RIVER NEAR LAS ANIMAS	PURLASCO	1961 – 2003	635	Conc=(4245.14)+(-332.65)*log(x)	0.62
ARKANSAS RIVER AT LAMAR	ARKLAMCO	1963 – 2003	510	Con=(4717.8)+(-355.25)*log(x)	0.69
BIG SANDY CREEK NEAR LAMAR	BIGLAMCO	1968 – 2003	262	Conc=exp((-.29e-3)*x+(8.10988))	0.52
ARKANSAS RIVER NEAR GRANADA	ARKGRACO	1981 – 2003	248	Conc=(5149.67)+(-347.61)*log(x)	0.73
FOUNTAIN CREEK AT PUEBLO	FOUPUECO	1963 – 2004	584	Conc=(3386.25)*x^0.1671	0.82

*Small number of data points

Water Rights

The Prior Appropriation Doctrine governs the amount of water that can be diverted at each diversion point in the Arkansas River basin. The Appropriation Doctrine establishes the amount and, in some cases, the timing in which the water can be diverted. The ability to divert water is based on the appropriation date of the right, i.e., the older the date, the higher the priority. At any given point in time, the original rights may have been modified in several ways. The final rights are the result of many transactions and decrees, which makes their determination an unwieldy task. The *LAR GeoDSS* implements a tool that, together with the MODSIM water rights extension, provides processing of the water rights database maintained by the CDWR for creation of the LARV water rights in the Geo-MODSIM network. The *LAR GeoDSS Water Rights Import* tool is accessed from the menu item *Arkansas Tools→Water Rights→Load from DB.* The tool requires a local copy of the CDWR water rights database in MS-Access database format. Figure 6.7 shows the MODSIM water rights extension interface with a sample of the imported water rights for the *LAR GeoDSS*. The text in the interface *Notes* column is generated during the import process with information on the processed transactions used to compute the final imported amount. The water rights extension creates the water rights modeling links associated with the imported rights directly into the Geo-MODSIM network, with each water right represented by a link conveying flows to the demand node representing the water user. Details about the CDWR water rights database, the import tool and its application to the *LAR GeoDSS*, as well as a summary of the processed water rights, are available in *LAR GeoDSS* user support (Appendix V – *Importing Water Rights from the CDWR Database*).

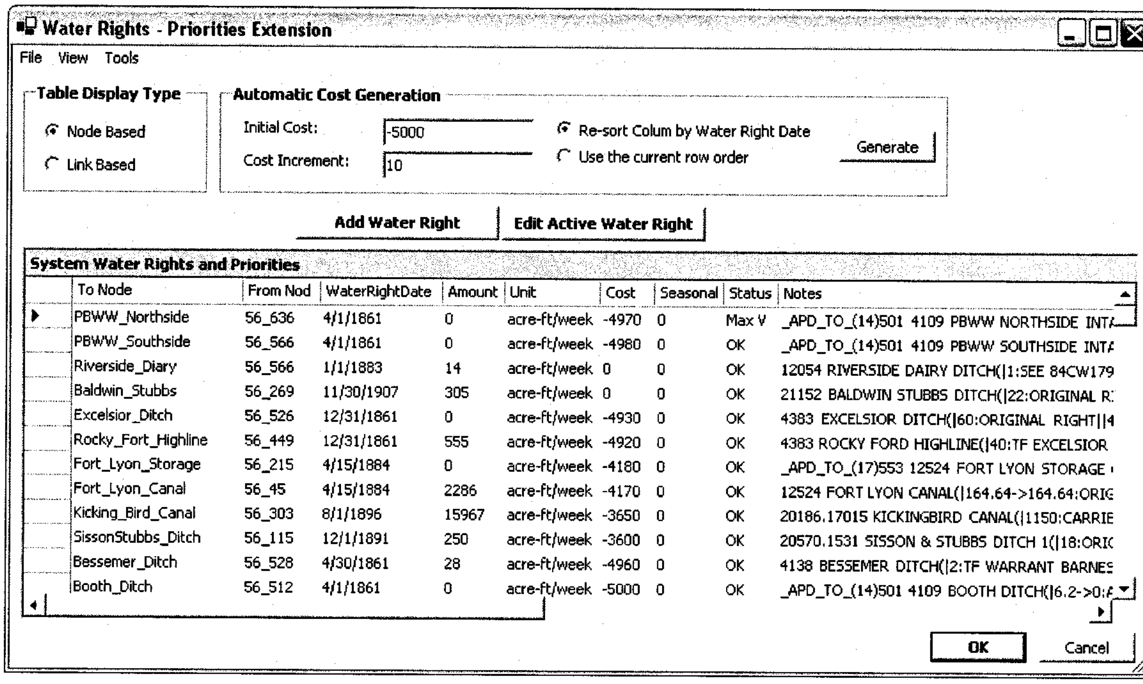


Figure 6.7 – MODSIM Water Rights Extension for the *LAR GeoDSS*

Alternate Points of Diversion

Alternate Points of Diversion (APD) are conditional diversion points in the basin where the original water right holder can take a portion of their right up to a decreed amount. The APD amounts and locations were modeled in the *LAR GeoDSS* using the historical diversion records. Since the diverted amounts at the APD were modeled as upper bounds on the high priority links that guarantee allocation of the APD diversions, the original right was consequently reduced by the amount diverted at the APD. The implementation of the APD in the *LAR GeoDSS* was automated by two utilities that build the modeling links and assign their link capacity time series from the diversion records database. The tools are accessed using the menu items: *Arkansas Tools→Create Network Links from Diversion DB→Alternate Points of Diversion* and *Arkansas Tools→Populate Time Serie→Fix Capacity to Alternate Pts of Diversion* respectively. The *LAR GeoDSS* allows the APD creation algorithm to be executed only once for each Base-Network to avoid processing errors by double counting the APD in the original rights. These tools use information coded into the link description by the import tool to associate water rights information with the diversions database. The APD active modeling links were renamed using the following format: "*ToNode* _APD_TO_(*WD*)*ID*". Table 6.7 summarizes the APD modeled in the *LAR GeoDSS*, where Table 6.7-A contains the links created during the diversion database analysis (i.e., not identified during the water rights import operation) and Table 6.7-B presents the links created during the water rights import process that are used in the APD modeling. Table 6.8-A contains the original rights that are adjusted for the current modeled period based on APD records. Table 6.8-B summarizes the modeled APD for information on the original right not found as result of the water rights import operation. If this original right was actually modeled in the *LAR GeoDSS*, an error was introduced by allowing diversion of the full amount at the original location, plus the recorded alternate diversion. Details on the *LAR GeoDSS* APD modeling procedures are available in Appendix V – *Modeling Alternate Points of Diversion*.

Table 6.7 – LARV Modeled APD Links

A.

APD Demand Node	Water Right Holder (WD)ID
Bessemer_Ditch	(14) 527
Bessemer_Ditch	(14) 600
Bessemer_Ditch	(14)3528
Bessemer_Ditch	(14)3537
StCharles_Mesa	(14) 527
StCharles_Mesa	(14) 533
StCharles_Mesa	(14) 600
StCharles_Mesa	(14) 666
StCharles_Mesa	(14) 3537
PBWW_Northside	(14) 537
PBWW_Northside	(14) 573
Lamar_Canal	(67) 5041

B.

APD Demand Node	Water Right Holder (WD)ID
PBWW_Northside	(14) 501
PBWW_Southside	(14) 501
Fort_Lyon_Storage	(17) 553
Booth_Ditch	(14) 501
Booth_Ditch	(14) 591
PBWW_Southside	(14) 591
PBWW_Southside	(14) 535
PBWW_Southside	(14) 589
PBWW_Northside	(14) 591
BWW_Northside	(14) 590
BWW_Northside	(14) 535
Bessemer_Ditch	(14) 527

Table 6.8 – Original Rights Adjustment and Errors Based on Alternate Diversion Records

A.

Adjusted Link Name (original right)	APD Node Name
56_45_Fort_Lyon_Canal	Fort_Lyon_Storage
56_512_Booth_Ditch_4	PBWW_Southside
56_512_Booth_Ditch_8	PBWW_Southside
56_512_Booth_Ditch_4	PBWW_Northside
56_566_PBWW_Southside_3	PBWW_Northside

B.

Water Right not found	APD Node Name	Admin No
WARRANT BARNES & BAXTER	PBWW_Northside	4109
WARRANT BARNES & BAXTER	PBWW_Southside	4109
WARRANT BARNES & BAXTER	Booth_Ditch	4109
WEST PUEBLO DITCH	PBWW_Southside	8127
WEST PUEBLO DITCH	PBWW_Northside	8127

Storage Water Diversion and Exchanges

Flows through diversion structures in the basin can include water diverted from storage contracts and the winter water program, where calls for storage water are based on the user's natural flow entitlement, water needed, and available storage water. Currently, the *LAR GeoDSS* does not implement storage account modeling since the *LAR GeoDSS* lacks information on users' available storage water and the additional complexity of modeling individual storage accounts does not provide additional benefit to the comparative evaluation of improved management alternatives. The modeling of storage water in the system was based on diversion records, similar to the approach used in the APD algorithm as explained previously. The *LAR GeoDSS* implemented modeling of special high priority links to consider total storage water represented as a single link or individual account diversions as multiple links. These special links are created using a *LAR GeoDSS* tool accessed in the menu item *Arkansas Tools→Create Network Links from Diversion DB→Storage Links to Demands.* This tool searches the diversion database for entries indicating water coming from storage to create the corresponding modeling links. A complementary tool assigns the historical diverted amount from storage contracts to the links capacity time series. This tool is accessed from the menu item *Arkansas Tools→Populate Time Serie→Fix Capacity to Storage Links*. Table 6.9 shows a list of users for which storage links are modeled in the *LAR GeoDSS*; along with the total diversion from storage modeled from April 1999 to October 2001 for each user. Additional details on the storage water modeling tools are found in Appendix V – *Modeling Storage Water Diversion.*

Table 6.9 – *LAR GeoDSS*-Modeled Storage Water Summary

User Name	Total Storage Usage [Acre-ft]	User Name	Total Storage Usage [Acre-ft]
Amity_Canal	178541	Keesee_Ditch	8690
Animas_Town_Ditch	0	Kicking_Bird_Canal	0
Baldwin_Stubbs	0	Lamar_Canal	71217
Bessemer_Ditch	27527	Las_Animas_Consol	0
Buffalo_Canal	2473	Manvel_Canal	0
Catlin_Canal	28498	Otero_Canal	4627
Collier_Ditch	0	Oxford_F_Ditch	283
Colorado_Canal	464	PBWW_Northside	19278
Excelsior_Ditch	2315	Riverside_Diary	39
Fort_Bent_Canal	32585	Rocky Ford Ditch	0
Fort_Lyon_Canal	79083	Rocky_Fort_Highline	11163
Fort_Lyon_Storage	0	SissonStubbs_Ditch	0
Holbrook_Canal	50485	StCharles_Mesa	0
Hyde_Ditch	411	X-Y_Canal	0

Exchanges of natural flow for storage water are captured in this modeling methodology since there are records in the database of diversion from storage representing the exchange.

Additional releases from off-stream reservoirs for exchanges with the Arkansas River were modeled through the calibration structures when senior water rights were harmed due to the water exchange (e.g., Rocky Ford Ditch diversions affected by Holbrook Reservoir exchange with the Arkansas River).

Arkansas River Compact

The Arkansas River compact is an agreement between the states of Colorado and Kansas, signed in 1948, that ensures both states will receive their percentage share of the Arkansas River flow. John Martin Reservoir plays an important role in regulating flow in the Arkansas River for compliance with the compact. As a result of the 1980 operating plan, which was a resolution of the Arkansas River Compact Administration to provide more efficient utilization of storage water, reservoir inflows that are not immediately called are stored in separate storage accounts for Kansas and the ditches of Colorado Water District 67 according to rules specified in the resolution. The irrigation ditches of Colorado Water District 67 are located downstream of John Martin Reservoir. Water users can call for releases from their stored water independently according to their needs. The compact requires complex rules on storage and carry over water in the accounts. For this stage of the *LAR GeoDSS*, compliance with the Compact is achieved by guaranteeing historical deliveries to Kansas. These deliveries are based on available water in the Kansas account in John Martin, as accrued according to the compact rules. During the "what if" management alternative modeling, if water provided to the demand representing Kansas equaled or exceeded the historical flows then the simulation was assumed to be in compliance with the Compact. Since water entering John Martin Reservoir is subject to the storage rules imposed by the compact, implementing changes in historical amounts entering the reservoir require special attention. If flows entering the reservoir are reduced, there is a risk of not having enough water in the future to meet the compact requirements, however in this case the *LAR GeoDSS* will operate the system to provided the required data and replenish the historical level in the reservoir as soon as possible. In the case of larger flows entering the reservoir, unless the operational rules of the compact are modified, this water will be split in the storage accounts and will not be available for (1) replenish storage water used to meet water requirements in lower than historical flow periods, and (2) use additional generated water for water quality improvements by strategic releases. *LAR GeoDSS* simulations herein assume different degrees of flexibility in the Arkansas River compact operational rules.

Users in Colorado were treated differently in the management alternative simulations by assuming that these users participate in basin-wide programs to improve conditions in the basin. Therefore, diversions in Water District 67 were modeled as any other water use in the lower basin; i.e., these diversions are reduced from the historical diversions when considering scenarios for improving irrigation or reducing canal seepage. It was assumed that reductions from the historical diversion for these users are not a violation of the compact, and that the unused water can be used/stored by an implementation program. The priority assigned to the demand node for modeling Kansas flow requirements was set to 50, giving it a higher priority over other users in the system in order to secure compact compliance.

The Kansas water demand was represented at the USGS Coolidge, KS, gauging station (ARKCOOKS) located at the farthest downstream node of the Geo-MODSIM network. A special structure was implemented in the *LAR GeoDSS* to handle additional flows to Kansas during the modeling of the management alternatives. This structure creates a System Sink node (named "__SYSTEM_SINK"), which has a low priority (i.e., 2200 in simulation and 4850 in calibration) and a high demand node linked to the node ARKCOOKS (Figure 6.8). The structure is automatically added to the Geo-MODSIM network at run time. Flow to the system sink was added to the flow to the ARKCOOKS station to represent the total flow to Kansas in the *LAR GeoDSS* simulations.

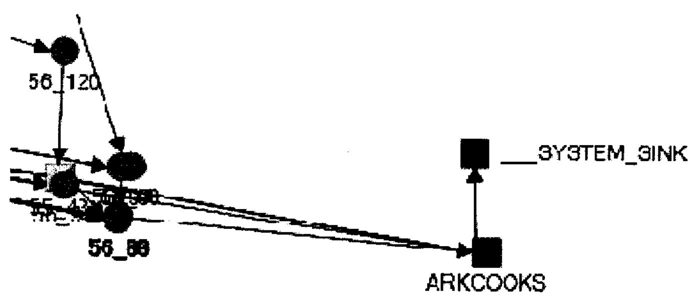


Figure 6.8 – System Sink in the *LAR GeoDSS* network

Canals Interfaces

The concept of a *terminal interface* was implemented for modeling the canals in order to allow water to flow downstream of the diversion demand node to be captured at a terminal *flow-through* demand node that can implement a fractional return to the river system. *Terminal interfaces* are nodes located at the ends of the canals through which return flows can occur. Special terminal interfaces, *reservoir interfaces*, are implemented when the canal flows into a reservoir. *Reservoir interfaces* allow a fraction of the water in the canal to be stored in the reservoir or a specified time series of flows to be stored. The interfaces were implemented in the data-model non-storage feature class using the *ARK_Type* field. Nodes in this interface were assigned with *ARK_Type* = 'Terminal Interface' and

ARK_Type = 'Reservoir Interface', depending on the type of interface. Both interface types handle a return flow fraction as specified in the data-model *ARK_Return* field. At run time, the *LAR GeoDSS* converts the interface nodes and the diversion demands to *flow-through* demand type nodes. In addition, the *LAR GeoDSS* sets the *flow-through* demand node parameters accordingly, where diversion demands are assigned with a return fraction of 1 and interfaces are set with the data-model specified fraction. Though the return fraction could be estimated for canals with available measured returns, the current *LAR GeoDSS* uses the calibration structures to account for canal returns.

Carrier Diversion Structure

Some diversions act as carriers of water for other users, usually for storage purposes. These diversion points are marked in the diversion database with the field *T*=3. A Carrier Diversion Structure is implemented in the Geo-MODSIM network to allow diverting water for downstream demand nodes. The structure consists of a *bypass credit link* that connects the downstream and upstream nodes of demand nodes representing diversions (Figure 6.9). The flow through the *bypass credit link* is considered as part of the diversion flow (i.e., surface water delivered to the demand node). This link is assigned with zero cost allowing downstream demands on the canal (e.g., *reservoir interfaces*) to call for water through the bypass link.

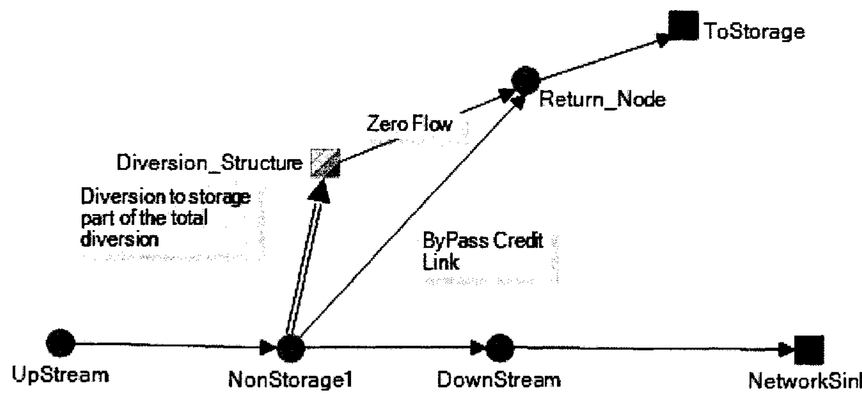


Figure 6.9 – Carrier diversion structure diagram

The carrier link is named using the name of the diversion demand node, followed by "_CarrierByPass_" and the ID of the user for which the water is carried. A summary of the diversion structure IDs that have entries with T=3 in the database is shown in Table 6.10.

Table 6.10 – Carrier Structures Summary (based on diversion records)

WD	ID	Name	Carried For ID
14	533	BESSEMER DITCH (Municipal use in the St. Charles mesa water district)	527
14	540	COLORADO CANAL (Single Entry)	3537
17	648	FORT LYON STORAGE CANAL	3525
67	614	LAMAR CANAL	3512
14	539	EXCELSIOR DITCH	3537

The Fort Lyon Canal requires a manual entry in the diversion database to represent the Kicking Bird Canal diversion, which takes water through the Fort Lyon Canal diversion. Even though there are diversion records for the Kicking Bird Canal, no records are found in the database indicating that Fort Lyon Canal as the carrier. An entry is manually added to the diversions table to define this physical phenomenon for the *LAR GeoDSS* interpreter, but no data are needed for this entry (Table 6.11). An inconsistency could have been introduced by this measure if the Kicking Bird Canal diversions were not added to the database for total diversion at the structure since water passing through the bypass link is added to the diverted water.

Table 6.11 – Manual Diversion Database Entry for Fort Lyon to Create Water Carrier Structure

WD	ID	T	F	Name
17	553	3	555	FORT LYON CANAL

In this implementation, any water that flows through the diversion structure is used to supply the water demand. The structure guarantees supply to demands downstream of the diversion nodes, but lacks specification of ownership of the diverted water. This situation only appears in the case of Fort Lyon Canal diversion modeling where the Kicking Bird Canal uses the bypass link to convey only water in excess of the Fort Lyon diversion, using the Fort Lyon Canal diversion as supply.

Canal Seepage Modeling

Canal seepage field studies conducted in the Arkansas River Valley indicate significant seepage losses (Gates et al. 2006). Studies conducted in the regions both upstream and downstream of John Martin Reservoir show seepage losses ranging from 0.003 m^3/s per km (0.2 ft^3/s per mile) to 0.065 m^3/s per km (3.7 ft^3/s per mile). There is a high variability in the losses depending on the underlying soil types, water levels in the canals, adjacent ground water levels, and other factors. Canal seepage was modeled in the baseline using the user defined coefficient ($\bar{s}$), which computes seepage loss as a fraction of the diversion, where the calculated seepage is assumed to occur uniformly along the full length of the canal. As a first approximation to the overall system seepage, the *LAR GeoDSS* assumed a baseline seepage loss coefficient $\bar{s} = 0.2$ for all canals in the Valley based on the regional groundwater model average conveyance efficiency (E_C) (Gates et al. 2002).

Future refinements should adjust the coefficient based on detailed field studies and updated groundwater modeling results.

Stream-Aquifer Interaction Predictions in the Geo-MODSIM Network

Stream-aquifer interaction predictions were assumed to be an average result of the interaction as evenly distributed over the grouping area. Nodes in the data-model that intersect the grouping area are assigned to a corresponding return flow (or depletion) using a special construct. At the beginning of the simulations, the ANN module builds a *source-sink* structure with links in and out of all nodes flagged for conjunctive use modeling. The structure used the connecting link upper bounds combined with a large negative cost to model the predicted ANN returns/depletions. Figure 6.10 illustrates the source/sink MODSIM structure to provide calculated return flows to the stream network and depletions from the network.

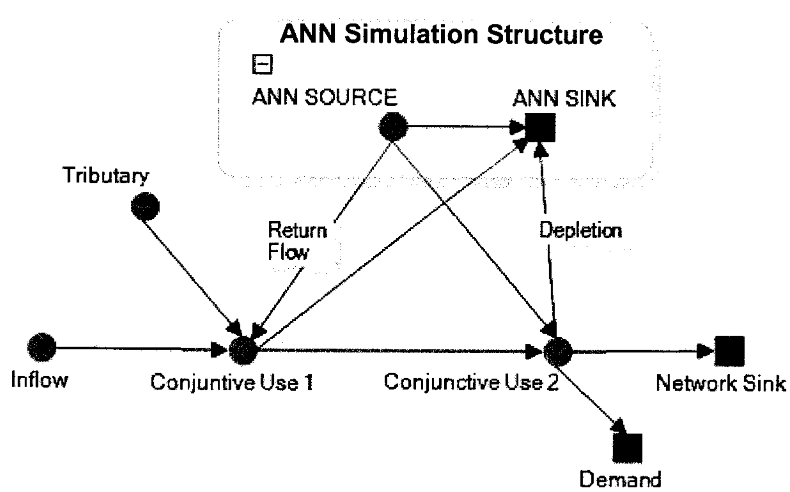


Figure 6.10 – ANN module MODSIM simulation structure

The ANN module was coupled with the MODSIM model to perform dynamic stream-aquifer interaction. The ANN module is initialized after MODSIM is initialized and the

ANN explanatory variables are calculated along with the MODSIM solution (each time step and iteration, if specified). Figure 5.1 shows a simplified diagram of the ANN module and MODSIM coupling. Detailed ANN-MODSIM coupling at run time is explained in Appendix III – *ANN predictions in Geo-MODSIM.*

Based on the ANN development results, the expected performance of the two sets of trained ANNs can be compared for the different reservoir operation scenarios. The *LAR GeoDSS* simulation was implemented with the *Dataset_A* ANNs (*AllScen_GWR_v8BArk_b* and *All_Scen_GWR_v8BTrib_c*). These ANNs have the more parsimonious structure of the two sets with less number of recurrent explanatory variables (see discussion on Chapter 4 – *The Simulation Challenge*).

Reservoir Salt Transport Model

The ANN module predicts concentrations at the John Martin Reservoir outlet based on reservoir inflow characteristics and initial and ending volumes (See Chapter 4). Since the flows and concentration explanatory variables are dynamically linked with the simulated values, the explanatory variables may diverge from the training values depending on the type of run and the reservoir operating rules. This module implements an option where the measured concentrations are used to build the ANN simulation dataset, which is recommended for ANN testing only. Improvement alternatives analysis uses the modeled concentrations for the reservoir salt transport allowing prediction of changes in the baseline transport based on the changes in the modeled explanatory variables.

The WQM was enhanced to integrate the ANN-based reservoir salt transport. If the reservoir salt transport model is active, the WQM overwrites the calculated concentrations at the reservoir outlet with the ANN predicted concentrations. Links immediately downstream of the reservoir outlet are assigned with the predicted concentrations. This type of transport modeling is expected to create an imbalance in the mass conservation at the node representing the reservoir outlet.

Simulation Scenario Manager

The custom *LAR GeoDSS Simulation Scenario Manager* implements the following management alternatives: (1) areal aquifer recharge reduction fraction per command area, (2) canal seepage reduction by canal system, (3) sub-surface drainage improvements per grouping area, and (4) vertical drainage pumping per grouping area. The Simulation Scenario Manager stores the management alternative preferences in the geo-database, where each alternative also contains information about the location of the groundwater modeling (MODFLOW-MT3DMS) output files and trained ANN export files. Figure 6.11 shows two sample views of the Simulation Scenarios Manager user dialog. The active scenario is selected using the combo-box list at the top, with several buttons to create, save and delete simulation scenarios. The lower portion of Figure 6.11-A displays the table for setting the drainage intensity and pumping increase percentage per grouping area. Figure 6.11-B shows the management alternative preferences for aquifer recharge reduction and canal seepage reduction per canal command area. Additional options include start and end dates of the irrigation activity (for aquifer recharge). Figure 6.11-C shows an area of the Simulation Scenario Manager displaying flags and preferences for the *LAR GeoDSS* project such as: (1) global irrigation activity deep percolation fraction, (2) active modules (water quality and ANN), (3) reservoir transport model status, (4) run type, and (5) calibration preferences (calibration network name).

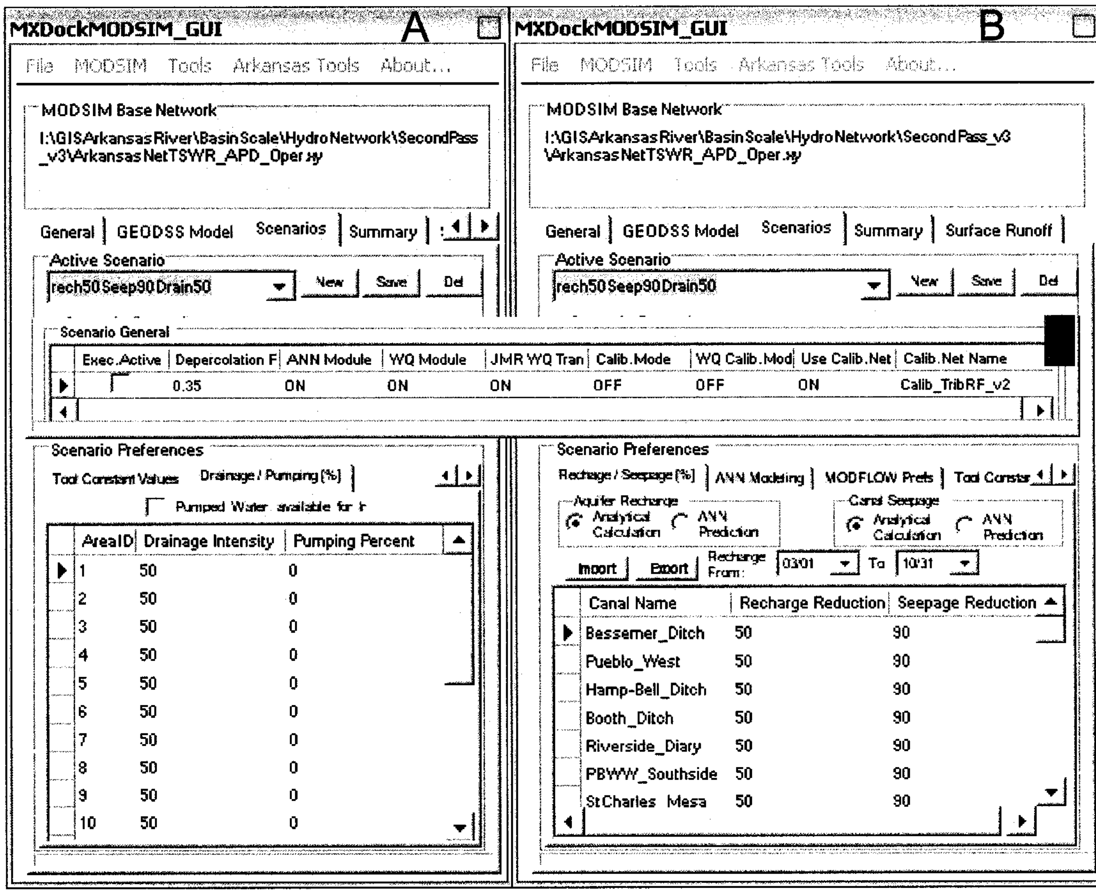


Figure 6.11 – Simulation Scenario Manager User Dialog Sample (*LAR GeoDSS*)

Figure 6.12 shows user dialog views for the management alternative-based ANN, MODFLOW-MT3DMS preferences. In Figure 6.12-A, the user specifies the ANN export file locations and names for the stream-aquifer interaction (both main river and tributaries). The user enters (Figure 6.12-B) location and name of the MODFLOW project (**.mfs*), the MODFLOW river cells file (**.riv*), and the MT3DMS output (**.con*) files associated with each management alternative.

A tool to assist users in setting management alternative preferences for all canal command areas or all grouping areas is also available in the Simulation Scenario Manager (Figure 6.13).

Simulation Scenario Analysis Tool

This section describes a set of custom tools implemented for the *LAR GeoDSS* to expedite results processing and analysis. The tools assist in checking, analyzing and comparing basin-wide simulations results. The summary tools are accessed at the "Summary" tab in the *LAR GeoDSS* interface.

The first tool summarizes each run individually by providing four tables containing the system-wide summary of network inflows, MODSIM calculated channel losses, water demand, water shortages, measured flow with shortages (for calibration control) and flow checks on high priority links. The high priority links, i.e., the storage contracts and APD modeling links, are checked to corroborate that they are flowing at maximum capacity at all times, as expected in the algorithm. The check summary table includes links flowing at partial capacity at any point of the simulation. The network calibration structures were designed to provide any additional water for satisfying all demands and therefore no shortages are expected at any time. The water shortage summary is valuable since it identifies total water shortages in the system per time step, as well as detailed locations of the shortages for a particular time step. Figure 6.14 shows a sample of the summary tables generated in the *LAR GeoDSS* interface (Summary Tab).

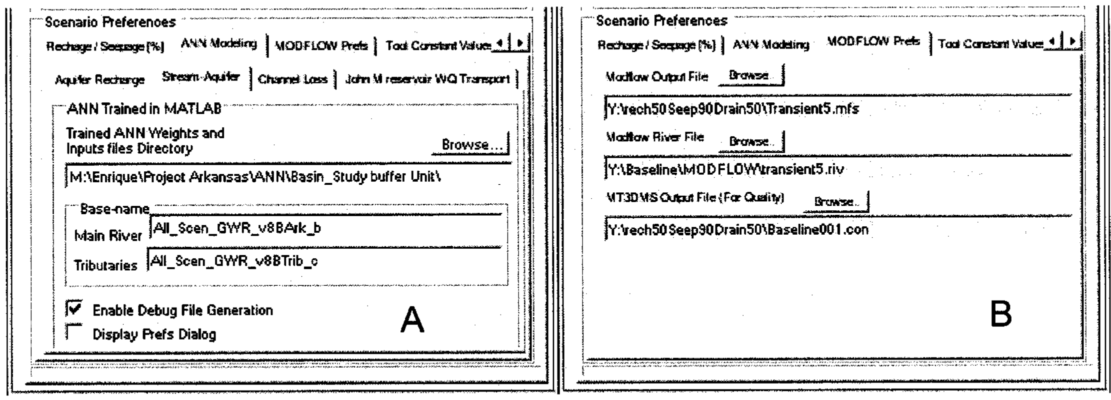


Figure 6.12 – Simulation Scenario Manager ANN and groundwater modeling preferences sample

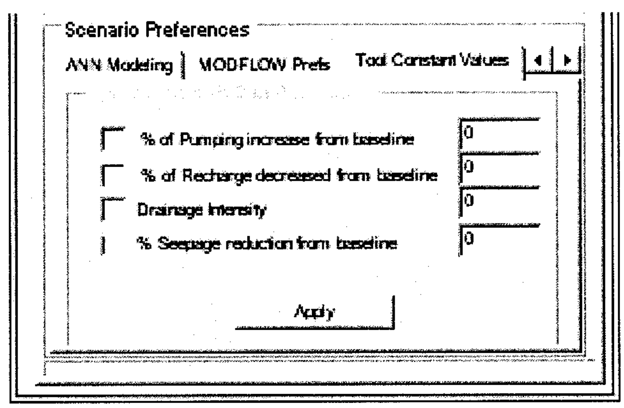


Figure 6.13 – Simulation Scenario Manager batch preferences setting tool

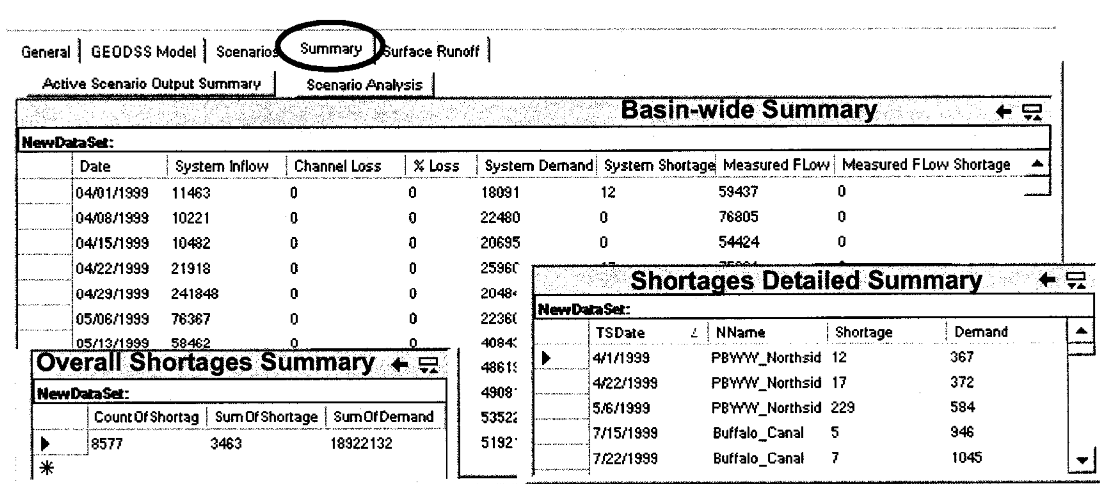


Figure 6.14 – Single run performance summaries in *LAR GeoDSS*

The second tool compares the system-wide baseline performance with the results from alternative management scenarios. Comparison is based on (1) reservoir storage in Pueblo and John Martin Reservoirs, (2) flows and concentration summaries at key points in the basin, (3) Arkansas River compact compliance, (4) stream-aquifer interaction modeling summary, and (5) calibration flows summary. Figure 6.15 shows the simulation scenarios comparison interface as displayed in ArcMap. The interface consists of four areas: Area 1 allows selection of the available simulation scenario to include in the analysis and selection of the baseline simulation; Area 2 displays Pueblo and John Martin Reservoir storage plots (only Pueblo Reservoir is shown in Figure 6.15); Area 3 provides a tabular summary of total water in storage at the end of the simulation, total diversions, diversion shortages, diversion average concentrations, canal seepage (as calculated by the simulation scenario manager), total flow and average flow concentrations to Kansas, total return flow/depletions and corresponding average concentrations (as grouped according to main river and tributaries), total calibration flows (i.e., inflows and outflows), and John Martin Reservoir salinity transport indicators (i.e., total mass inflows/outflows and the corresponding ratios). Area 4 in Figure 6.16 provides comparative plots of basin-wide total diversions, shortages, seepage losses, return flows, river depletions, Arkansas River compact flows to Kansas and average concentrations for each time step.

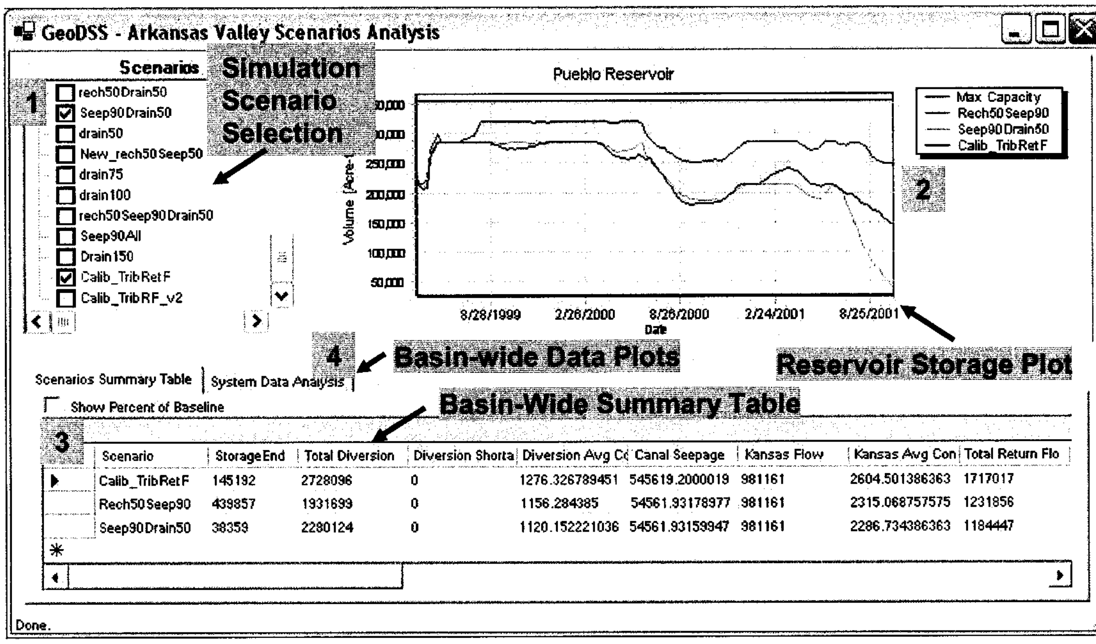


Figure 6.15 – Interface of the simulation scenarios comparison tool in ArcMap

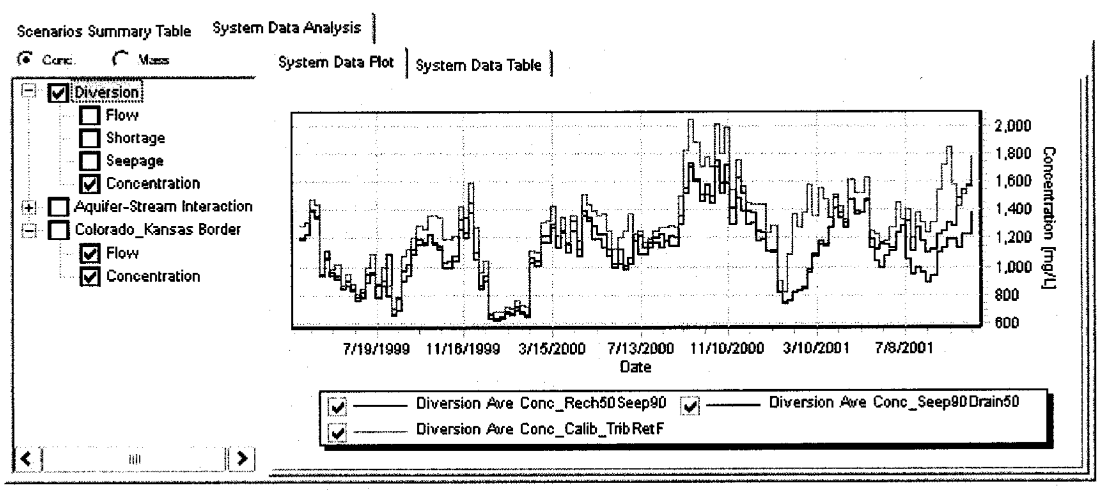


Figure 6.16 – System-wide result summary plots interface

MODEL CALIBRATION

A weekly time step was selected for this case study, providing a compromise between accurate water rights modeling and adequate representation of the system for planning purposes. Although errors could be introduced in the allocation of water by not accounting for the daily variability, weekly time steps provide reliable modeling of the system yield. The *LAR GeoDSS* Base-Network was populated with weekly historical flows from April 1999 to October 2001 extending over the same period as the available regional-scale groundwater model. The baseline modeling system enabled the ANN-based stream-aquifer interaction modeling methodology and the WQM includes the John Martin Reservoir salt transport model as presented in Chapter 4. This modeling system was calibrated for both water quantity and quality using the *LAR GeoDSS* hydrologic calibration tools and procedures introduced in Chapter 5. Calibration structures were created to provide local gains and losses, and unmeasured concentrations for inflows were adjusted to match as closely as possible the measured concentrations at the control points. The calibration network used the historical volumes in the reservoirs as storage targets for computing calibration flows that resulted in replication of the historical reservoir storage levels.

Modeling Underlying Characteristics

Since a weekly time step was selected for network flow simulation, it is assumed that flow routing can be neglected in the network stream and canal reaches. This means that changes in storage in the connecting elements of the model representing streams and canals are neglected in this modeling system, i.e., the flow entering a link is equal to the flow leaving the link. At the nodes, complete mixing was assumed for water quality modeling; therefore, the concentration of flows leaving the node are assumed to have concentrations equal to the total mass entering the node divided by the total volume flowing into the node during the given time step.

Although potentially large errors could exist in the flow measurements, one of the main assumptions in the model calibration was that the surface water measurements are accurate.

Local gains and losses were calculated based on the measured surface water flows with the ANN predicted stream-aquifer interaction considered as known input/output to the system and gains and losses calculated accordingly to alleviate any discrepancy with the measured flows.

With specification of a weekly time step, the travel time of water through the flow networks was assumed to be less than one week, i.e., water travels from any point in the system to another within the time step interval. Travel times are a function of stream and river reach conditions. Based on the average-flows and a representative rate of travel from Pueblo Reservoir to John Martin Reservoir as given by Livingston (1978), one week is approximately the time that would take an average-flow release from Pueblo Reservoir to reach the state line (approximately 185 (miles) downstream at 0.9 (h/mi)).

Some additional assumptions in the Arkansas River basin modeling: (1) no diversion data were assigned to the Pueblo Board of Water Works Southside intake diversion, since diversions at this point in the system are apparently linked to the Riverside Dairy (id = 536); (2) Booth Ditch was not modeled since no records of diversion exist after 1973. Stream-aquifer interaction was neglected in the tributaries or portions of the Arkansas River outside of the groundwater modeling grouping areas, or for those portions of the tributaries outside of the irrigated valley. Aquifer-stream interaction was not considered for: (1) Purgatoire River, (2) Chico Creek, (3) Fountain Creek, (4) Two Butte Creek and (5) the Arkansas River upstream of the ARKMOFCO station. In the Purgatoire River, the portion of the stream that would be modeled is surrounded by irrigated fields and is located in a groundwater modeling grouping area covered for the most part by John Martin

Reservoir. In this case, the ANN explanatory variables lose their meaning. The location of the PURLASCO gauging station provides baseline flows that include groundwater return flow close to the reservoir inlet, thereby reducing the effect of this modeling restriction. For the water quality modeling, it was assumed that the flow-concentration relationships developed for stations with sporadic data adequately represent the concentrations of the average weekly flows. The values computed at the station are used in the modeling regardless of the measurement availability.

Calibration Results and Analysis

Since the calibration network was set up to meet all historical flows in both demands and control points (gauging stations), water shortages occurring during calibration required careful analysis. The *LAR GeoDSS* simulation analysis tool was used to check for water shortages. Table 6.12 shows the summary of water shortages amounts during a calibration run. In this case, water shortages for the three nodes were caused by missing or misinterpreted water rights, exchanges or ADP at these points that generated these errors.

Table 6.12 – Calibration Water Shortage Summary

NName	SumOfShortage
Buffalo_Canal	144
Excelsior_Ditch	12
PBWW_Northside	3307

With the exception of minor round-off errors, the flow checks at high priority links confirmed that the storage water contracts and APD adequately model these components, thereby leaving the available natural flow rights to satisfy the remaining water demands in the system.

During calibration, both Pueblo and John Martin Reservoirs operate at the defined storage targets (Figure 6.17 and Figure 6.18).

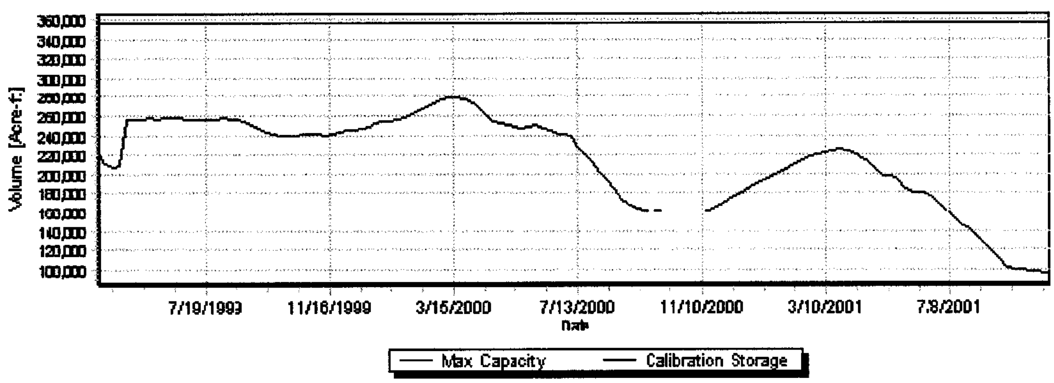


Figure 6.17 – Pueblo Reservoir storage content calibration run

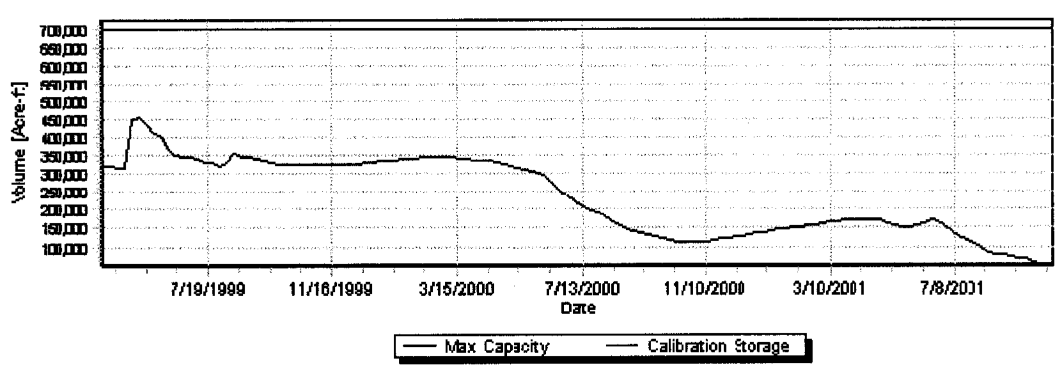


Figure 6.18 – John Martin Reservoir storage content calibration run

Since all control points in the system, i.e., gauging stations, exactly met the measured flows; each of these nodes (*flow-through* demands) provided the downstream reach with exactly the measured flow each time step.

Analysis of the calibration network results pointed to problems with the diversion records for Water District 14 and 17. Gains and losses larger than expected in the reach led to identification of missing inflow or outflow data. From this analysis, it was concluded that diversion records for the structures with double WDs (Table 6.3) are split between the districts for water year 1999, whereas the storage diversion records seem to be duplicated during the same period. Rules to implement these findings were coded into the *LAR GeoDSS* data import tools.

Calibration Results per River Reach

The calibration analysis was carried out using the control points for the surface drainage areas. ArcHydro tools were used to construct the surface drainage areas for the control points in LARV and these drainage areas were used to group the system nodes by calibration reach for analysis of gains and losses. The calibration reach was named after its downstream station. Figure 6.19 shows the control point surface drainage areas used for grouping nodes in the calibration analysis.

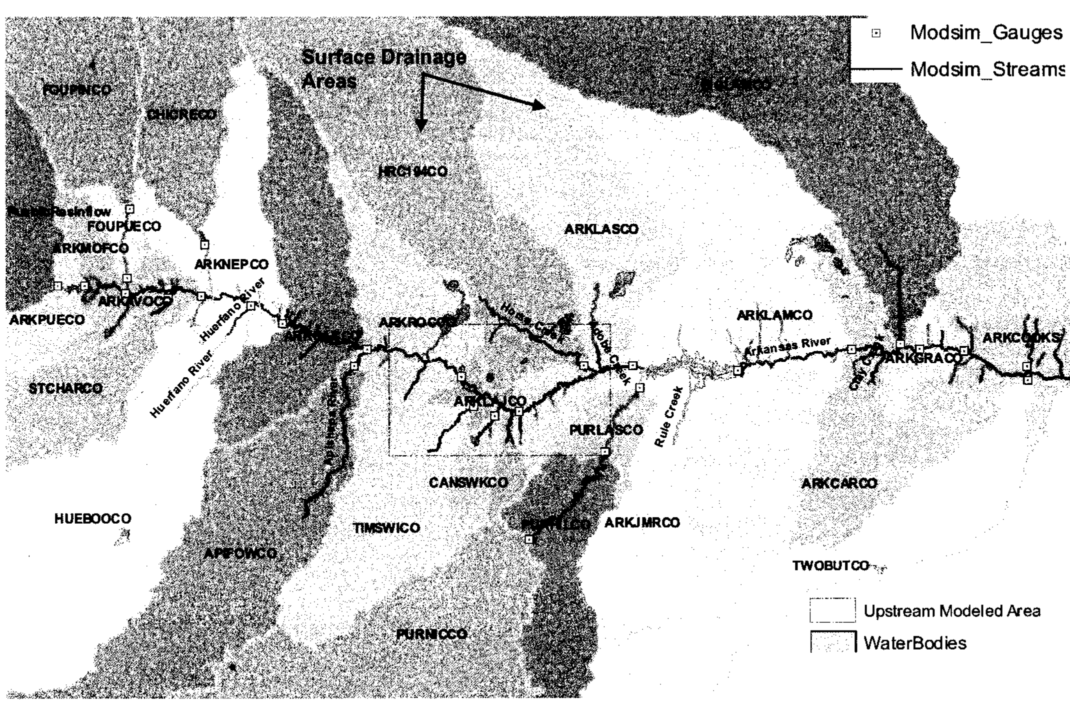


Figure 6.19 – Control points surface drainage areas

The system inflows and outflows were analyzed per calibration reach, representing water handled by the calibration structures to match measured flows at the control points. Figure 6.20 and Table 6.13 present a summary of total inflows and outflows during the simulation period for reaches marked as system sources, i.e., reaches corresponding to the most upstream gauging stations. Inflows to Pueblo Reservoir were not included in the summary plot since this was a calculated inflow, modeled using the upstream source link of the ARKPUECO intermediate reach. Total inflow is on the order of 1.3 million of acre-ft during the simulated period. The summary shows that the largest tributary inflow to the Arkansas River occurs at Fountain Creek (FOUPINCO reach). Excess water in source reaches occurs when the ANN-predicted return flows upstream of the gauging station are larger than the measured flows. As a result of the calibration procedure, the source nodes release flows that exactly match the downstream measured amounts. System source reaches with modeled stream-aquifer interaction include: APIFOWCO, BIGLAMCO, CANSWKCO, HRC194CO, HUEBOOCO, STCHARCO, TIMSWCO, and WILDHOCO.

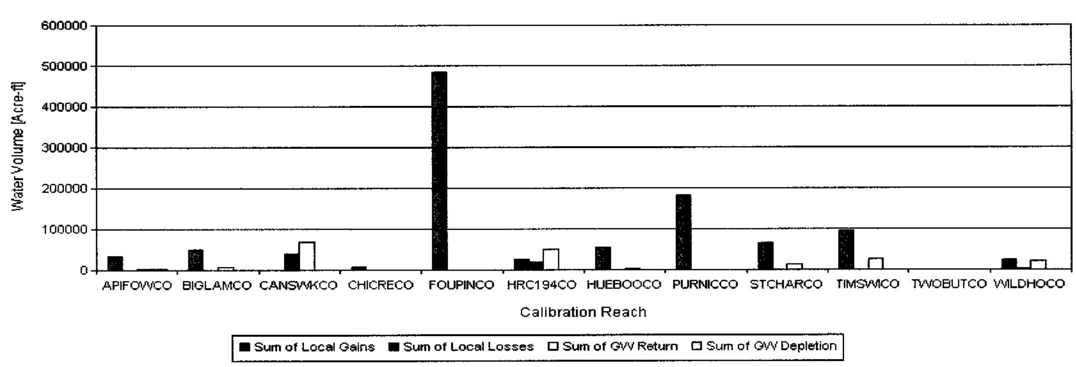


Figure 6.20 – Measured system inflows and outflows at the system source reaches

Table 6.13 – Summary Calibration System Sources Inflows/Outflows

Reach	Inflows [Acre-ft]	Losses [Acre-ft]	GW Return Flow [Acre-ft]	River Depletion [Acre-ft]
APIFOWCO	33356	6	3365	3914
BIGLAMCO	50346	0	8073	783
CANSWKCO	214	39965	69040	0
CHICRECO	6961	0	0	0
FOUPINCO	482964	0	0	0
HRC194CO	26227	17995	49101	1315
HUEBOOCO	55925	369	3143	1126
PURNICCO	181259	0	0	0
STCHARCO	67104	1142	12560	619
TIMSWICO	94531	0	27616	0
TWOBUTCO	290	0	0	0
WILDHOCO	24612	3741	20190	26

The system local gains and losses were totaled per calibration reach, where the gains were located at the upstream ends of the reach and the losses were located at the downstream station. Figure 6.21 and Table 6.14 shows the calibrated system gains and losses per calibration reach. Stations showing gains and losses simultaneously in the summary indicate that, over time, the reach switches between gaining and losing conditions. An example of this gain and loss behavior during the simulated period is shown in Figure 6.22 (reach ARKLAJCO). In this example, predominant gaining and losing conditions appear to occur in consecutive time steps, and rarely occur simultaneously. Although, the calibration structure avoids unnecessary addition and removal of calibration water, the locations of the water demands and reach inflows might require additional water upstream, while at the same time removing water downstream. Detailed gain and loss summary plots for all the control points are given in Appendix V. The reach ARKPUECO shows local gains corresponding to the Pueblo Reservoir inflows since the upstream source node (*PuebloResInflow*) is not provided with measured inflows; i.e., inflows are auto-calculated to match the reservoir operation, reach diversions and measured flow at the downstream station.

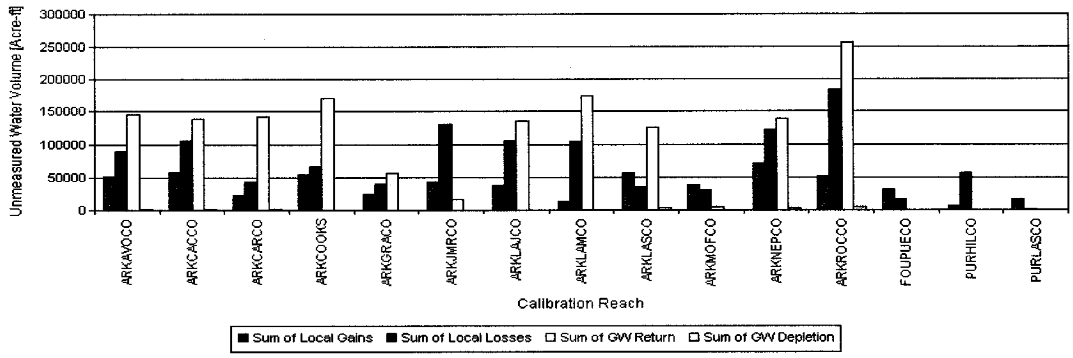


Figure 6.21 – Calibrated system gains and losses

Table 6.14 – Summary Calibration River Reach Gains and Losses

Reach	Inflows [Acre-ft]	Losses [Acre-ft]	GW Return Flow [Acre-ft]	River Depletion [Acre-ff]
ARKAVOCO	51008	88889	146561	1857
ARKCACCO	57871	106697	138753	2359
ARKCARCO	23561	43767	142386	2349
ARKCOOKS	55004	66578	171483	209
ARKGRACO	24283	39655	55579	0
ARKJMRCO	42493	130123	17331	144
ARKLAJCO	37362	106691	136002	270
ARKLAMCO	13753	104441	174324	0
ARKLASCO	55859	34560	126476	3461
ARKMOFCO	37929	29769	5561	0
ARKNEPCO	71190	123271	138644	3012
ARKPUECO	1366378	0	0	0
ARKROCCO	51770	184051	257563	4489
FOUPUECO	30786	16126	0	0
PURHILCO	5880	56176	0	0
PURLASCO	17335	1174	0	0

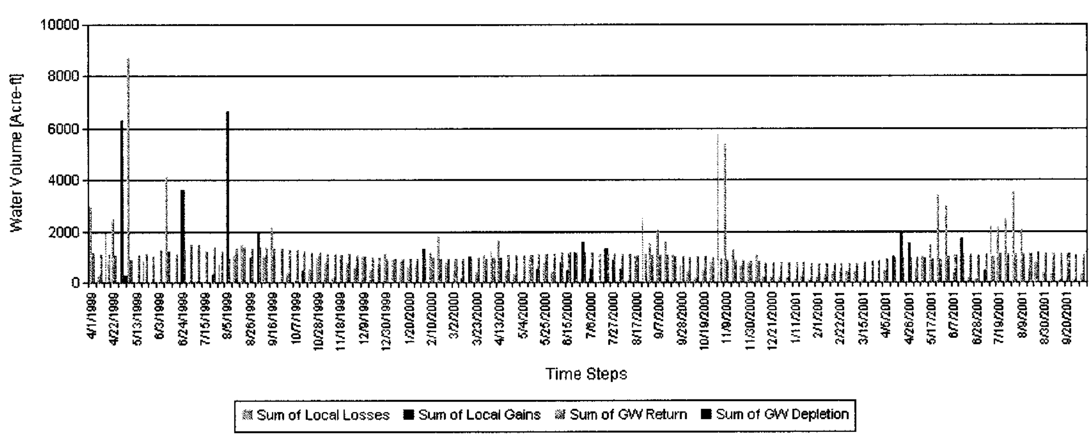


Figure 6.22 – Local gains and losses during calibration for reach ARKLAJCO

Stream-Aquifer Interaction Modeling Analysis

In this section, the ANN predicted aquifer return/river depletions were analyzed using the *LAR GeoDSS* calibration tools. Stream-aquifer interaction was processed using Geo-MODFLOW to evaluate performance of the trained ANN in the *LAR GeoDSS* based on: (1) the quality of the predictions with unknown initial conditions and (2) the effect of using imperfect previous time step explanatory variables; i.e., using previous time step predictions as explanatory variables rather than the "perfect" modeled values. For the former, the ANN module priming procedure (described in Chapter 3) was tested for providing the ANN with reasonable initial conditions for the modeling. The ANN stream-aquifer interaction prediction was analyzed using two different grouping elements: (1) the stream-aquifer modeling grouping areas and (2) the calibration reaches. The first grouping provides direct comparisons with the MODFLOW-MT3DMS modeling, whereas the second allows comparison of the predictions against the measured gains and losses.

Geo-MODFLOW and ANN Predictions

The ANN was trained to represent return flows and salt loadings for the grouping areas, assuming they were evenly distributed within the grouping area nodes. Therefore, a weak correlation is expected when comparing the ANN results with the MODFLOW modeled values at a higher resolution than the grouping areas; e.g., comparing individual MODSIM nodes and the corresponding upstream link MODFLOW return flows. Earlier experimentation using predictions of flows/loadings per unit length in the grouping areas showed little improvement in matching MODFLOW modeled return flows. However, this approach proportionally distributes return flows and salt loadings among short and extremely large segments.

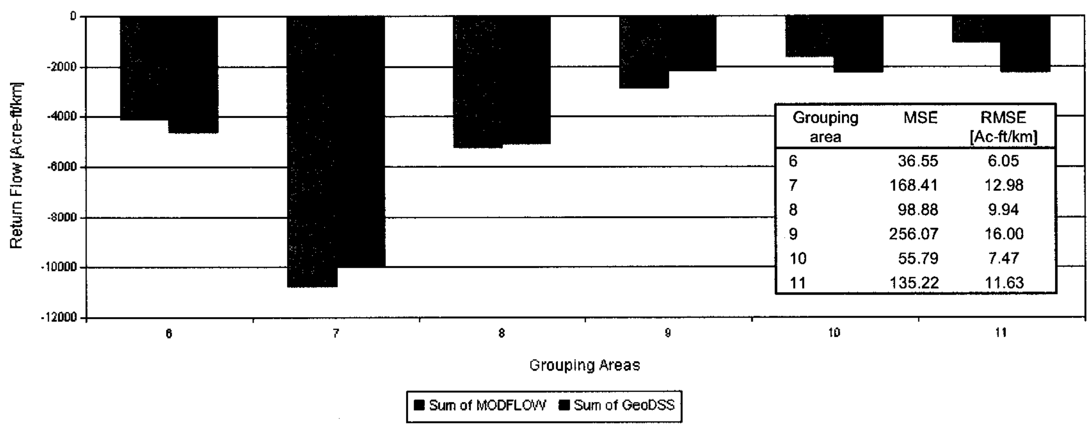
ANN modeling grouping areas-based Analysis

The *LAR GeoDSS* stream-aquifer interaction modeling was analyzed by aggregating the predictions and MODFLOW-MT3DMS modeled values for the interaction modeling grouping areas (Figure 4.2). Geo-MODFLOW summarized the modeled interaction per grouping area to be compared with the *LAR GeoDSS* values. The net aquifer return flow with negative sign represents a MODFLOW's aquifer output; for comparison, *LAR GeoDSS* was plotted to match the MODFLOW sign. The results were analyzed separately for the Arkansas River and tributaries.

Arkansas River Stream-Aquifer Interaction

The mean squares error (MSE) quantifies the amount by which an estimator differs from the true value of the quantity being estimated. MSE is computed as the expected value of the squared difference between the observed and predicted values (Lehmann and Casella 1998). The root mean squared error (RMSE) is computed as the square root of the MSE, being for unbiased estimators the standard error in the same units of the quantity being estimated. Figure 6.23 shows a comparison of the MODFLOW-MT3DMS and *LAR GeoDSS* total net return flow estimated for the five modeled grouping areas in the Arkansas River, including the MSE and RMSE for each region. The overall average expected root mean error = 10.68 acre-ft/km. The predictions improved after the first modeled year, where Figure 6.24 shows that larger errors occurred in the first year of the simulation. The average RMSE over the second and third years = 6.84 acre-ft/km.

The average predicted concentration of return flows to the Arkansas River over the modeled period was compared with the MODFLOW-MT3DMS modeled concentrations (Figure 6.25). Except for grouping area 11, there was a slight tendency to under estimate the concentrations. Figure 6.26 shows the concentration RMSE per grouping area and per year, with the overall average RMSE = 200 mg/L. Similar to the flow prediction performance, the largest errors occurred during the first year with respect to the MODFLOW-MT3DMS modeled concentrations, with the average RMSE over years 2000 and 2001 = 132.82 mg/L.



Grouping area	MSE	RMSE [Ac-ft/km]
6	36.55	6.05
7	168.41	12.98
8	98.88	9.94
9	256.07	16.00
10	55.79	7.47
11	135.22	11.63

Figure 6.23 – Arkansas River total net return flow comparison for the modeled grouping areas

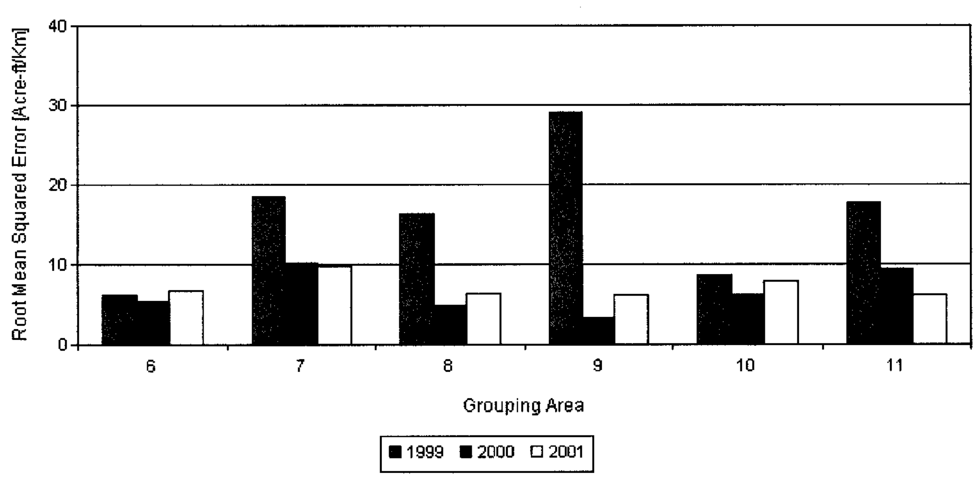


Figure 6.24 – Aquifer return flow RMSE per year per grouping area

Both the *LAR GeoDSS* net returned volume and concentration results show agreement with the corresponding MODFLOW-MT3DMS modeled values in the grouping areas. The year 1999 exhibits the largest errors, resulting in considerable degradation of the overall prediction performance.

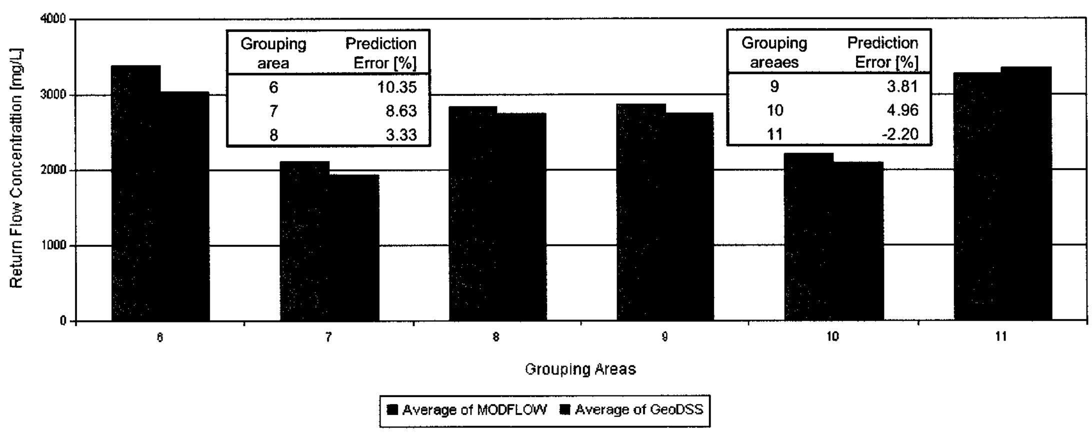


Figure 6.25 – Arkansas River Average concentration comparison for modeling grouping areas

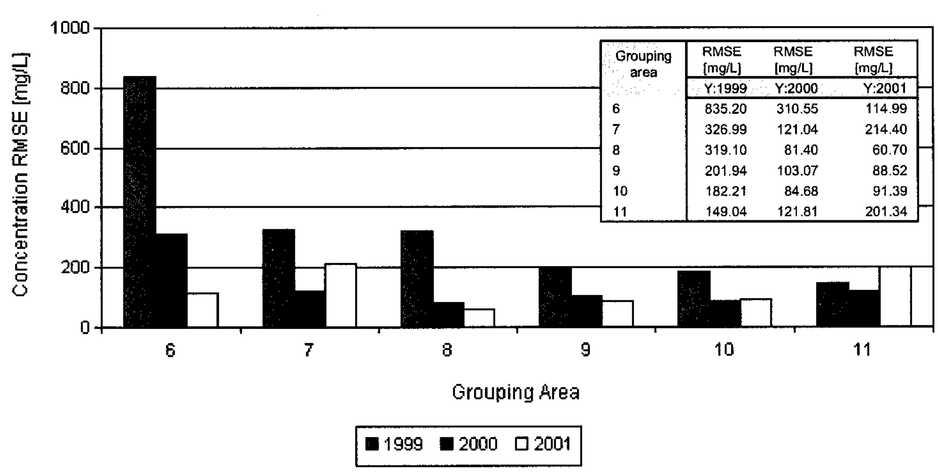


Figure 6.26 – Arkansas River Concentration RMSE per grouping area per year

The basin-wide stream-aquifer modeling results are summarized in Figure 6.27. The total basin-wide return flow predictions seem reasonable based on the range of the total modeled grouping area predictions. Slightly larger return flows were predicted in the upper half of the grouping areas, where the average net return flows for grouping areas 1 to 10 = 1634.51 acre-ft/km, as compared with the average net return flows for grouping areas 11 to 20 = 1357.80 acre-ft/km.

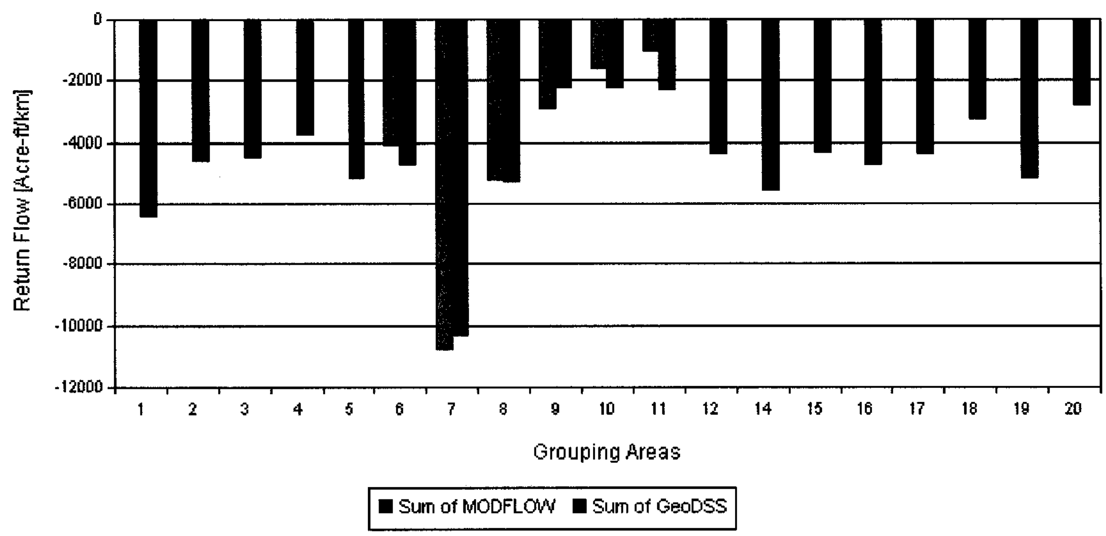


Figure 6.27 – Basin-wide Arkansas River stream-aquifer interaction modeling summary

Tributaries stream-aquifer interaction

The *LAR GeoDSS* tributary return flows and concentrations were compared with the MODFLOW calculations. Figure 6.28 shows total net aquifer return flows during the three-year calibration period for those grouping areas with tributary modeling. The average RMSE for the four-modeled areas = 8.98 acre-ft/km. The prediction error analysis per year is shown in Figure 6.29, with the largest error of 12.77 acre-ft/km (RMSE) occurring in grouping area 6 during the first year of simulation and 6.48 acre-ft/km over the remaining two calibration years.

With the exception of grouping area 11, the *LAR GeoDSS* average predicted concentrations tend to be lower than the MODFLOW modeled concentrations in all the grouping areas (Figure 6.30). In this case, analyzing the concentration error per calibrated-year shows no clear difference in the concentration prediction performance for the grouping areas (Figure 6.31). It is noticed that in both analyses (i.e., for individual years and the overall performance), there is a sequence of larger concentration prediction errors in the grouping areas in the downstream direction. It is believed, however, that this behavior would not provide a reasonable basis for generalizing predictions over the entire basin.

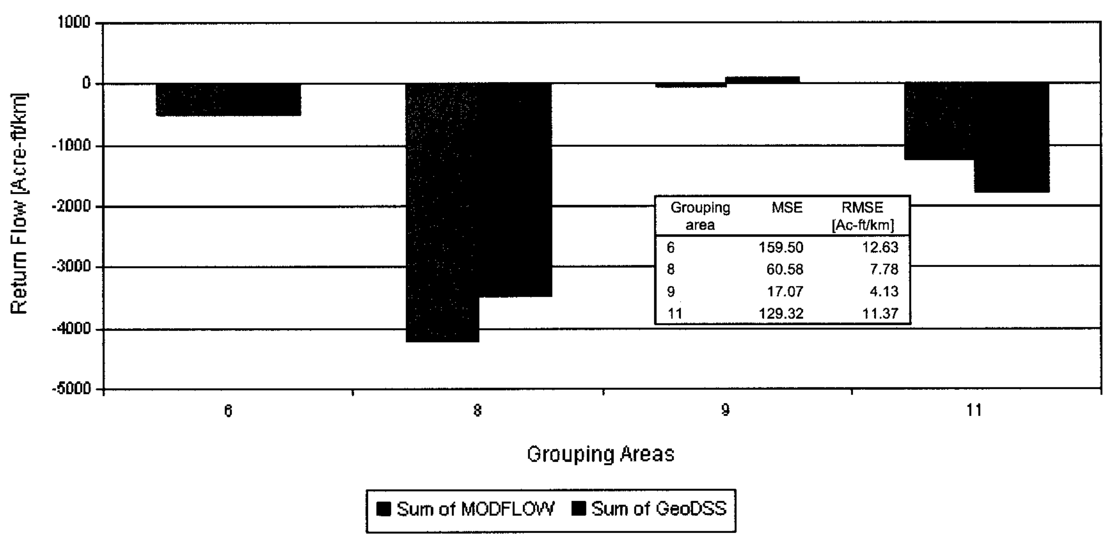


Figure 6.28 – Tributary total net return flow comparison for the modeled grouping areas

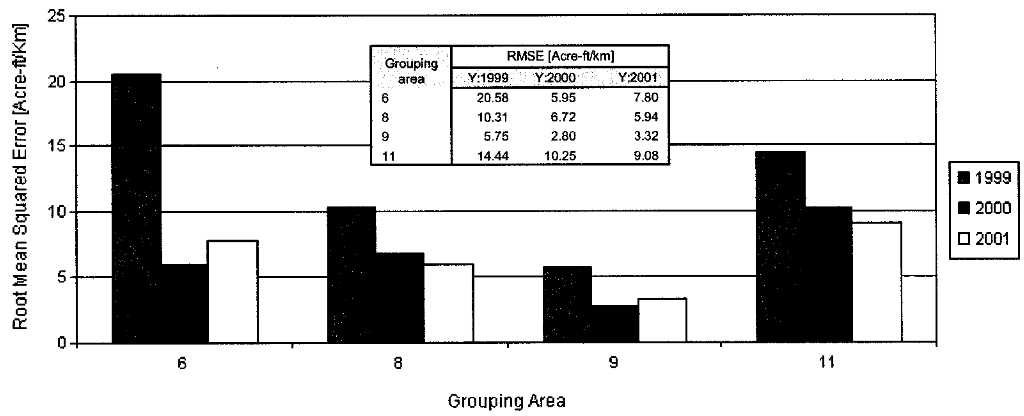


Figure 6.29 – Tributary aquifer return flow RMSE per year per grouping area

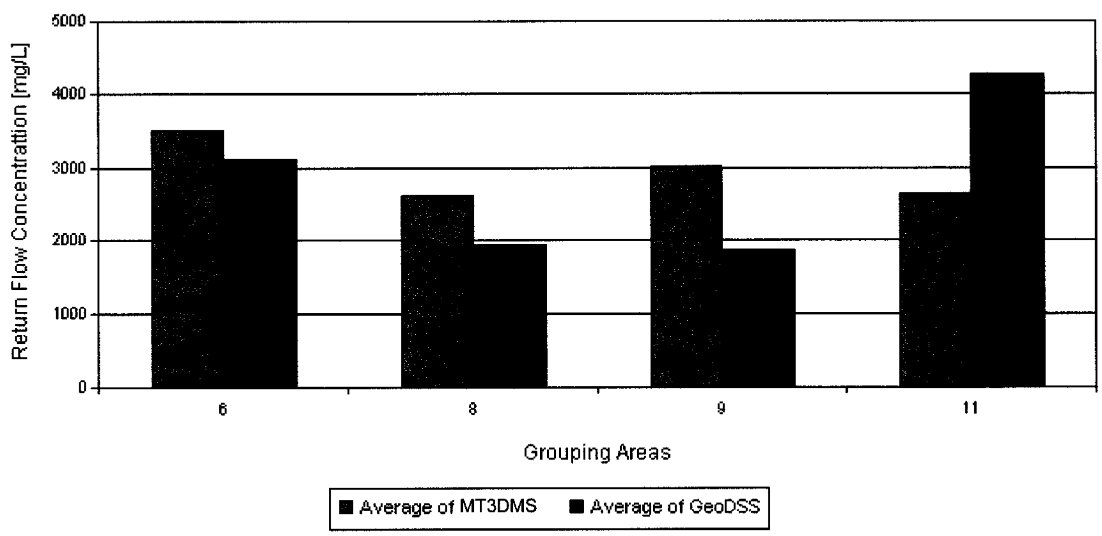


Figure 6.30 – Tributary Average concentration comparison for modeling grouping areas

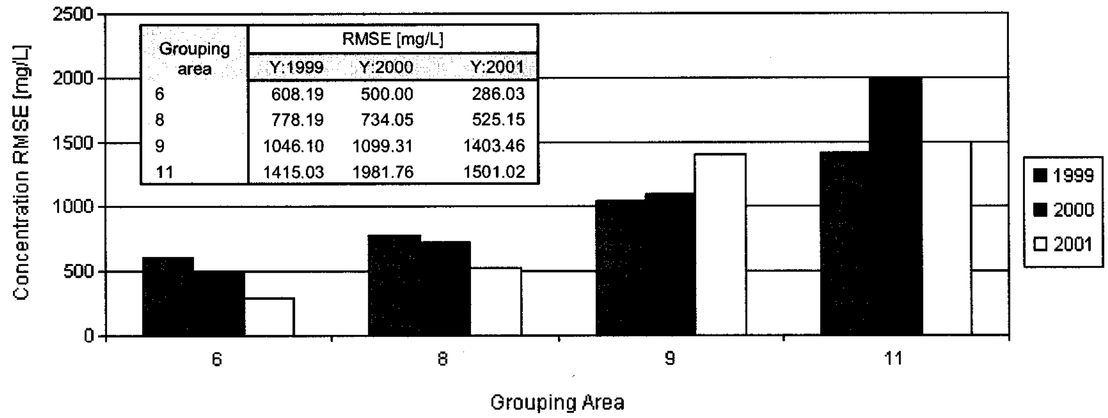


Figure 6.31 – Tributary Concentration RMSE per grouping area per year

The basin-wide tributary stream-aquifer interaction shows that total predictions for MODFLOW-MT3DMS non-modeled grouping areas are in the modeled range, with larger return flows predicted in the downstream region of the modeled area (Figure 6.32). Grouping Area 7 was excluded from the ANN training because less than 1 km of tributary length is intercepted by the grouping area; therefore the return per unit length is not representative. The *LAR GeoDSS* prediction was only calculated if the length is greater than 1 km, i.e., grouping area 7 stream-aquifer interaction prediction was omitted in the *LAR GeoDSS* modeling.

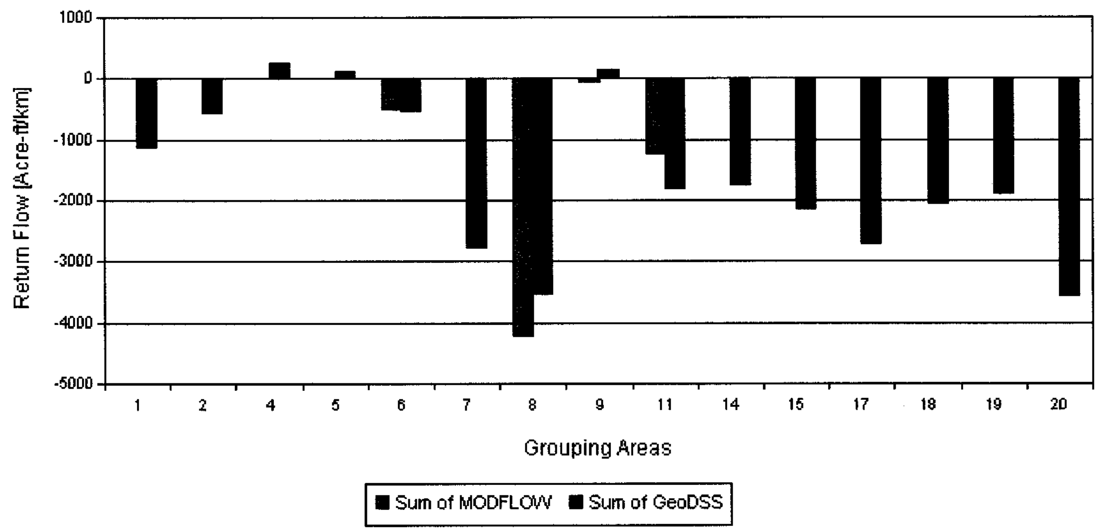


Figure 6.32 – Basin-wide tributary total net return flow summary

Analysis based on Calibration Reaches

The goal of the calibration is to estimate the network unmeasured gains and losses. Without specifically modeling the stream-aquifer interaction in the *LAR GeoDSS*, the computed gains and losses are based on streamflow measurements that include the aquifer return flows and river depletions. An analysis of the calibration results with and without the ANN stream-aquifer modeling provided information for the ANN prediction analysis.

System Source Reaches Analysis

The system source analysis without stream-aquifer interaction gives the surface measured inflows to the system at their corresponding gauging stations (Table 6.15). Analyzing Figure 6.33 and Figure 6.20, the reaches APIFOWCO, BIGLAMCO, HUEBOOCO, STCHARCO, WILDHOCO, and TIMSWCO show a groundwater contribution that is a portion of the surface measured based gains. Reaches CANSWKCO (Crooked Arroyo) and HRC194CO (Horse Creek) show a groundwater contribution larger than the measured flow in Figure 6.33, indicating a possible over-prediction of return flows in these tributaries. Since both CANSWKCO and HRC194CO were partially contained in the groundwater modeled area, it was possible to check the MODFLOW-MT3DMS results to examine the situation.

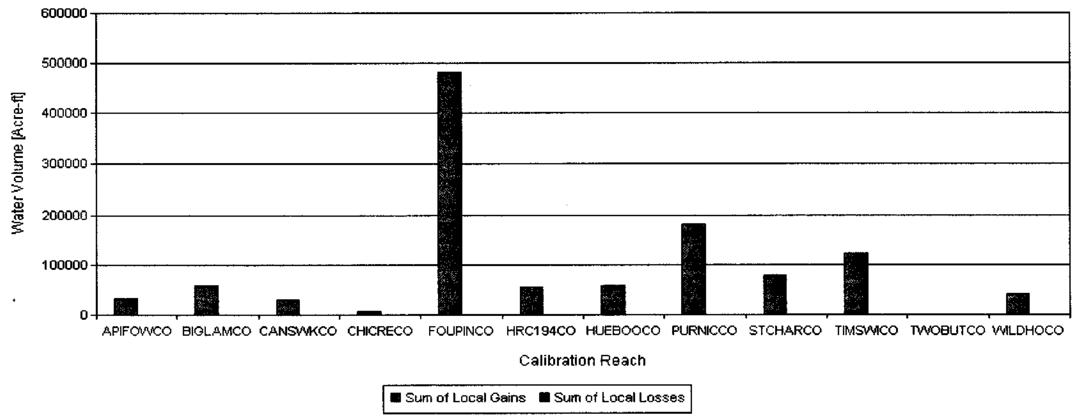


Figure 6.33 – System source reaches inflows without stream-aquifer modeling

Table 6.15 – Net System Source Reaches Inflow Summary

Reach	Inflows [Acre-ft]	Losses [Acre-ft]
APIFOWCO	32801	0
BIGLAMCO	57636	0
CANSWKCO	29289	0
CHICRECO	6961	0
FOUPINCO	482964	0
HRC194CO	56018	0
HUEBOOCO	57573	0
PURNICCO	181259	0
STCHARCO	77903	0
TIMSWICO	122147	0
TWOBUTCO	290	0
WILDHOCO	41035	0

The Geo-MODFLOW tool was used to extract the MODFLOW return flow volumes to Crooked Arroyo upstream of the station. Comparison of the measured amounts, the MODFLOW return flows and the ANN predicted return flow volumes show that over-prediction occurred at Crooked Arroyo in the *LAR GeoDSS* simulation (Figure 6.34). The ANN predictions for tributary return flows (per unit length of tributary reach) in the grouping area represent the MODFLOW total return flow in the tributaries of grouping area

8 quite well (as shown in Appendix II – *All_Scen_GWR_v8Trib_a Overall and Baseline Predictions Analysis*). However, since the volume is evenly distributed over the nodes on the tributaries in grouping area, the small tributaries (e.g., Crooked Arroyo) could have received a portion of the return flows that was disproportionally large for their size, while large tributaries (e.g., Timpas Creek) received a smaller return flow for their size. Figure 6.35 supports this hypothesis by showing the larger MODFLOW return flows and smaller *LAR GeoDSS* predictions at Timpas Creek (i.e., larger tributary in grouping area 8). The limitation illustrated in this exercise reiterates the expected low accuracy of stream-aquifer interaction predictions at smaller scales than the modeling grouping areas.

Figure 6.35 shows that the MODFLOW return flow volumes were generally larger than the measured gains, indicating a groundwater model over-prediction in Timpas Creek.

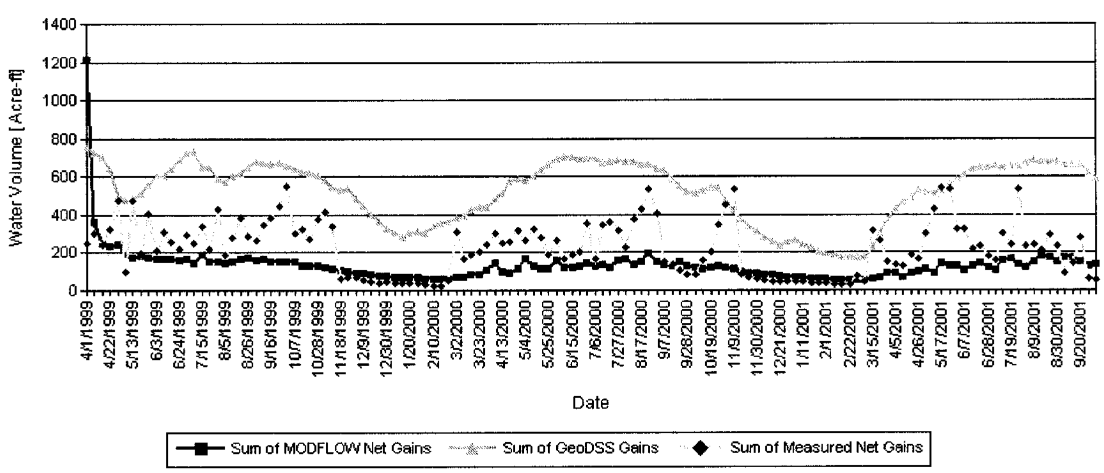


Figure 6.34 – Crooked Arroyo return flow comparison

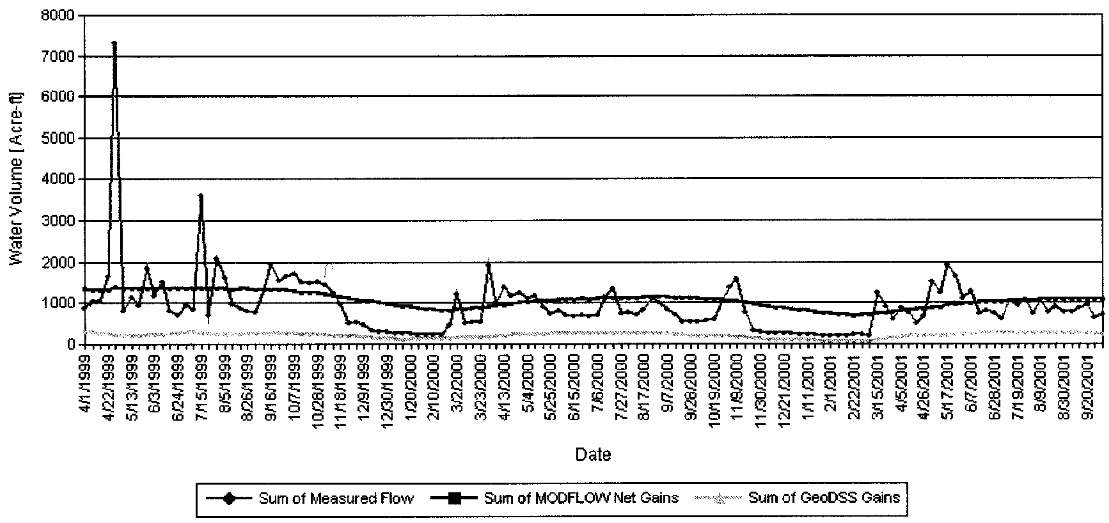


Figure 6.35 – Timpas Creek return flow check

The section of Horse Creek in the irrigated valley upstream of the station *HRC194CO* extends for about 23 km, with the length of the creek inside the two area-buffers about 11 km. Since the explanatory variables for stream-aquifer interaction were calculated only in the area-buffers, it is believed that the prediction was over estimated by using the entire length of the creek in the irrigated valley to predict the return flows. A more accurate prediction should be calculated with a shorter tributary length in the grouping area (approximately one-half); to provide better agreement with the measured values.

Intermediate Reaches Analysis

Network calibration was performed without the ANN stream-aquifer interaction, with the gains and losses calculated in this calibration exercise shown in Figure 6.36 and Table 6.16. Using the ANN stream-aquifer interaction modeling, the calibrated local losses increased in magnitude and the local gains reduced in magnitude, indicating that there could have been more total aquifer return flows than the anticipated from the surface water reach balance. This suggest that there could have been a timing issue in the return flows and possibly an over prediction. This analysis was affected by stations having zero flows (i.e., time steps without flow measurements) since the calibration algorithm opens the station to allow predicted flows to continue downstream. This situation forces the removal of additional losses at the immediate downstream control point. As a consequence, comparison of gains and losses with predicted return flows should combine these types of calibration reaches in order to be meaningful. As shown in Figure 6.21, stream-aquifer interaction was not modeled in Fountain Creek and the Purgatoire River (FOUPUECO, PURHILCO, and PURLASCO), so the results in Figure 6.36 show the outcome of upstream measured inflows in relation to the measured flows at these stations. The FOUPUECO reach reveal a losing/gaining section, PURHILCO shows a predominant losing reach, and PURLASCO indicate a predominantly gaining reach.

Table 6.16 – Calibrated Gains and Losses without Stream-Aquifer Interaction Modeling

Reach	Inflows [Acre-ft]	Losses [Acre-ft]
ARKAVOCO	156804	49981
ARKCACCO	137469	49901
ARKCARCO	104087	6152
ARKCOOKS	169804	10104
ARKGRACO	85154	23051
ARKJMRCO	50107	120550
ARKLAJCO	148037	27649
ARKLAMCO	96488	12852
ARKLASCO	148972	4658
ARKMOFCO	40858	27137
ARKNEPCO	133161	49610
ARKROCCO	132362	72550
FOUPUECO	30786	16126
PURHILCO	1664	55976
PURLASCO	21551	1374

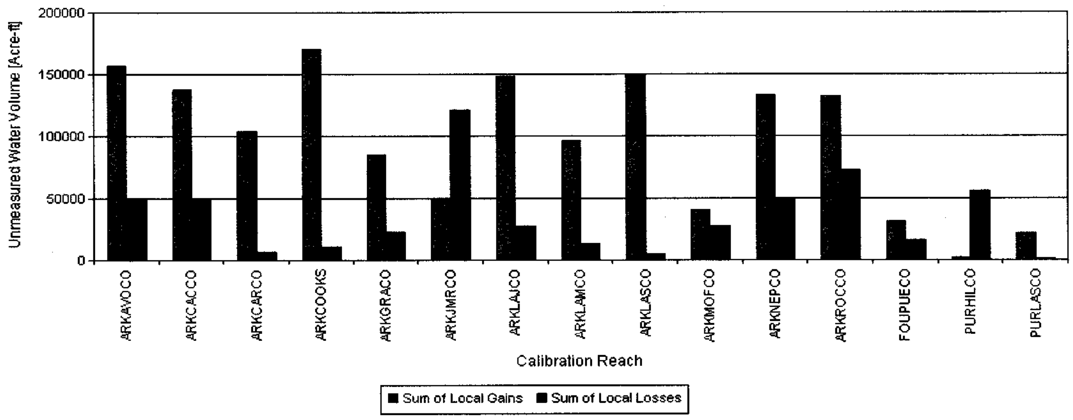


Figure 6.36 – System gains and losses for calibration without stream-aquifer interaction modeling

Three reaches intercept the groundwater modeled area: (1) ARKLAJCO, (2) most of the ARKROCCO and (3) a portion of the ARKLASCO. Stream-aquifer interaction predictions in these reaches were expected to be the closest to the MODFLOW-MT3DMS calculated interaction because they were located in the groundwater modeled area. Figure 6.37 shows net gains to these reaches from groundwater in both the MODFLOW-MT3DMS and *LAR GeoDSS* results as compared with the net gains calculated based on the surface water mass balance calculations. The results show that the *LAR GeoDSS* predictions were close to the MODFLOW net return flows, whereas the measurement-based net gains were more variable with positive (gains) and negative (losses) spikes. The average net gains during the modeled period in this reach were: 1283.60 acre-ft, 1028.27 acre-ft, and 945.19 acre-ft for MODFLOW, *LAR GeoDSS* and measurement-based respectively. Assuming that most of the measured gains were due to the groundwater-surface water interaction, the averages indicate a slightly tendency in MODFLOW and the *LAR GeoDSS* to over predict return flows in the long run.

Figure 6.38 shows the ARKROCCO reach comparison for the net gains calculated in MODFLOW, the *LAR GeoDSS* and the measurement-based surface water balance. The MODFLOW and *LAR GeoDSS* results show some agreement in their predictions, but the measurement-based mass balance show high variability and small agreement with the MODFLOW and *LAR GeoDSS* predictions. Since no measured data were available at ARKROCCO prior October 1999, the *LAR GeoDSS* disabled the station during this period to allow flows to continue downstream. This situation created losses in this reach that were caused by excess flows in the downstream reach, with gains in this period estimated to only meet historical diversions. The average net gains of MODFLOW, *LAR GeoDSS* and measurement-based mass balance were: 1283.60 acre-ft, 1917.22 acre-ft and 419.95 acre-ft respectively.

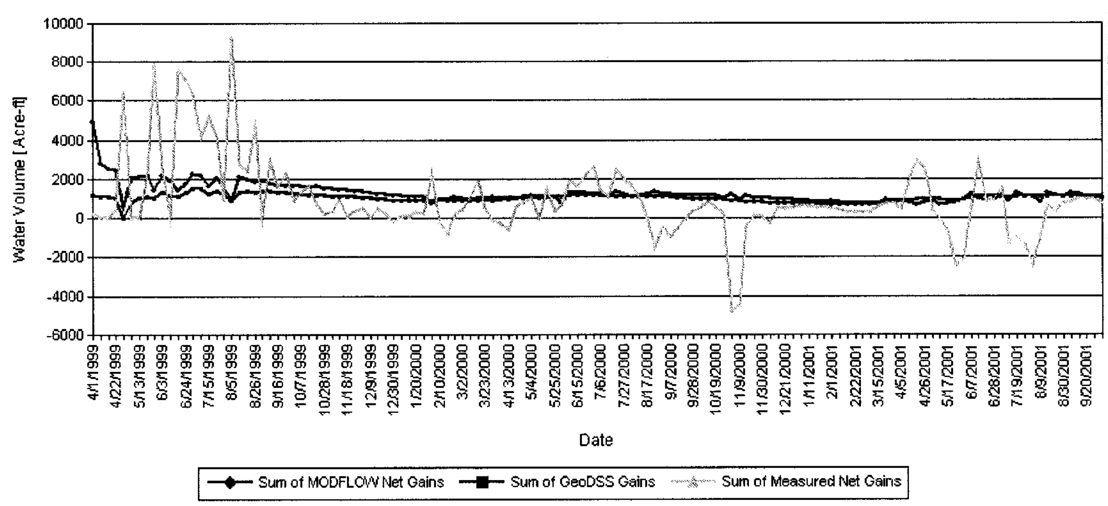


Figure 6.37 – ARKLAJCO reach return flow comparison

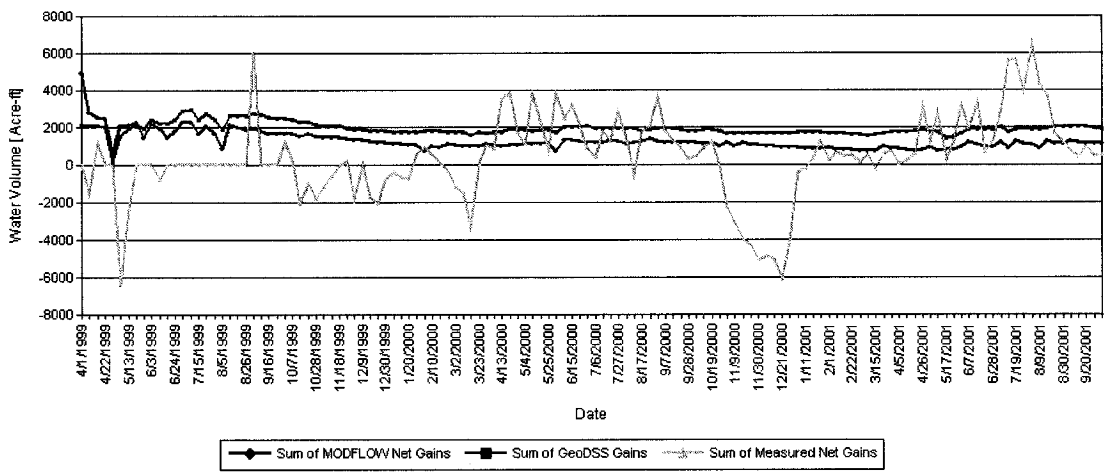


Figure 6.38 – ARKROCCO reach return flow comparison

Figure 6.39 shows a comparison of the modeled and measured net gains for the ARKLASCO reach, indicating a good agreement between net gains calculated in MODFLOW, *LAR GeoDSS* and measured surface water reach balance. The largest disagreement and highest variability was seen at the initial time steps of the modeling where large spikes were calculated from the measured data.

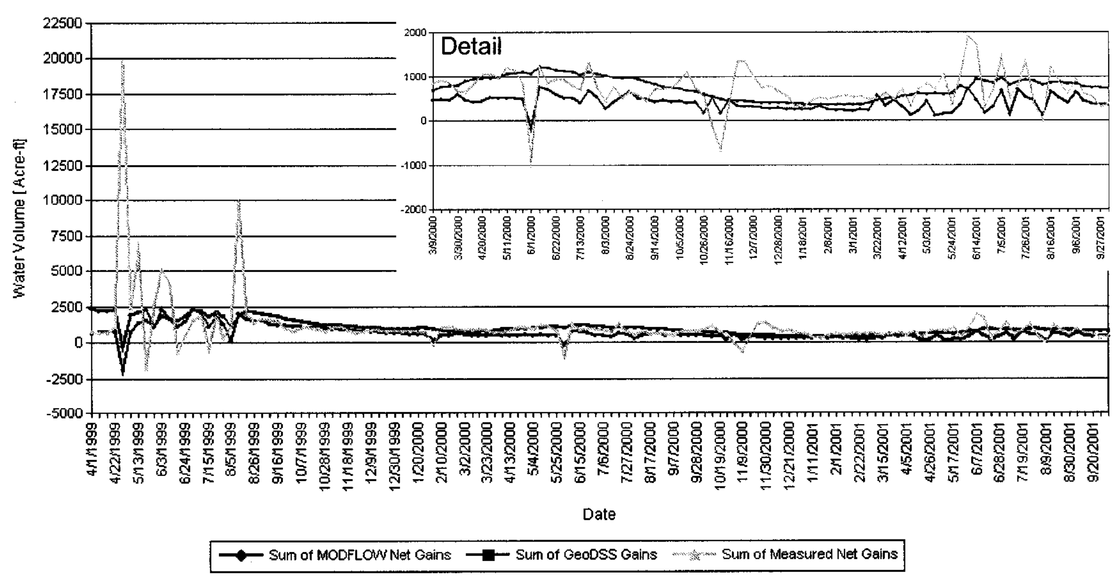


Figure 6.39 – ARKLASCO reach return flow comparison

Interpreting the comparison for ARKROCCO and ARKLASCO reaches requires taking into account that the entire area was not modeled in MODFLOW (see Figure 6.19). Consequently, the MODFLOW net return flows were calculated based only on the modeled cells. Detailed plots for the gains and losses per time step with and without the stream-aquifer interaction modeling are found in Appendix V – *Detailed Gains and Losses Analysis*.

Water Quality Calibration Analysis

During calibration, the ANN-predicted flows and concentrations were assigned as known system inputs and outputs. Consequently, an excess of modeled salt contributions from the aquifer to the surface system was compensated for during calibration by assigning low concentrations to reaches with unknown sources of salt mass; i.e., system measurements or calibrated inflows without concentrations defined. In this section, the calibrated water concentrations at the control points with measured specific conductance were compared with the measured values to evaluate the effectiveness of the semi-automatic calibration procedure. For the calibrated results, the cases where calculated concentrations were greater than the measured concentrations, the number and magnitudes of the unknown inputs were insufficient to dilute flows in the reach and match the measured value, recalling that unknown concentration limits lain between 0 and the maximum field observed value. In contrast, for cases where the calculated concentrations were lower than the measured concentrations, the unknown concentrations at the maximum allowed concentration were not high enough to elevate the concentrations in the reach to match the downstream-measured concentrations. Time series plots of the calculated and measured concentrations for all the reaches in the *LAR GeoDSS* can be found in Appendix V – *Water Quality*

Calibration Detailed Analysis. The root mean squared error (RMSE) was calculated with the predictions for all the modeled time steps at the water quality control points in the basin (Figure 6.40). The RMSE values give a sense for the magnitude of the expected error in the water quality calibration. The errors were larger in the more downstream stations since the calibration errors accumulate in the direction of the flow; i.e., the modeled concentration was continuously computed through of the control points, propagating the unmatched concentration downstream until there were enough unmeasured inputs to overcome the discrepancies with measured concentrations downstream.

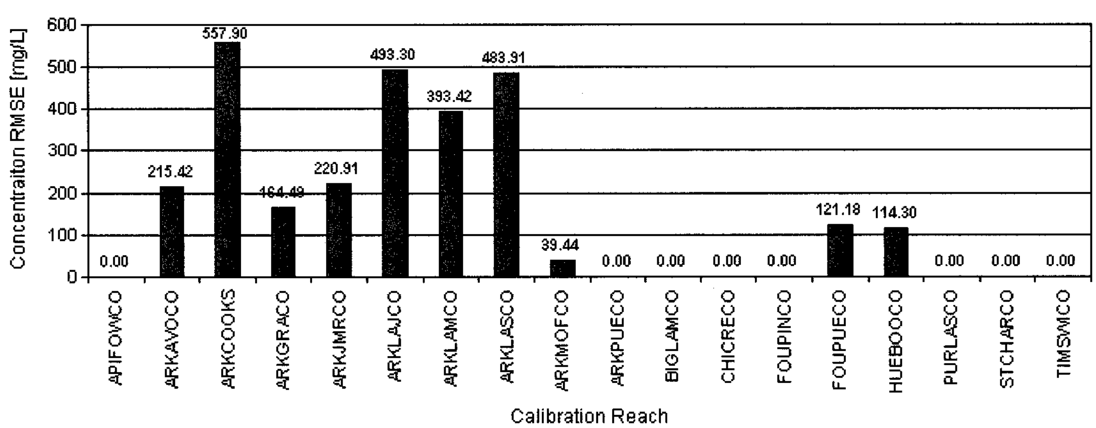


Figure 6.40 – Root Mean Squared Error (RMSE) at the *LAR GeoDSS* control points

The average concentration at the control points provided a measure of over or under prediction of concentrations in the calibration results. Figure 6.41 and Table 6.17 present a summary of the statistics of the predicted and measured average concentrations at the control points in the modeled Arkansas River basin. Based on the average concentrations, reaches ARKKAVCO, ARKGRACO, ARKLAJCO, ARKLASCO and HEBOOCO tend to be over-predicted, whereas concentrations in ARKCOOKS, ARKJMRCO, ARKLAMCO, ARKMOFCO and FOUPUECO were general under-predicted. The coefficient of determination was also calculated for the concentration predictions at the gauging stations. For most of the control points, the proportion of the variability accounted for in the calibration procedure ranged from 0.6 to 1, except for the FOUPUECO station that r^2=0.35. Even though the FOUPUECO calculated concentrations match the measured concentrations in several time steps, these cases where concentrations were not matched resulted in under-prediction that produced a low error r^2 overall. The measured and predicted averages were separated by only by 60 mg/L and the standard deviations were similar, indicating that the predictions were reasonable despite the low coefficient of determination.

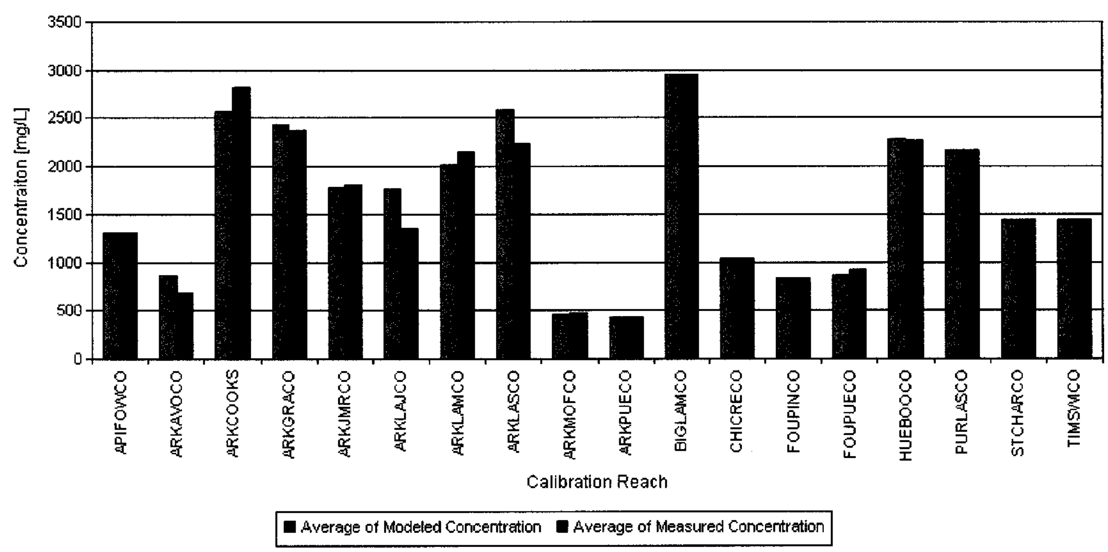


Figure 6.41 – Average calibrated and measured concentration comparison

Table 6.17 – Calibrated Concentration Statistics per Control Point

Reach	Modeled Concentration		Measured Concentration			
	Average [mg/L]	Standard Deviation	Average [mg/L]	Standard Deviation	Average Difference	R^2
APIFOWCO	1304.05	220.16	1304.05	220.16	0.00	1
ARKAVOCO	865.05	244.67	689.36	152.82	-175.69	0.87
ARKCOOKS	2569.88	489.73	2815.04	700.76	245.16	0.57
ARKGRACO	2426.54	410.45	2367.64	343.00	-58.90	0.87
ARKJMRCO	1786.23	344.14	1807.87	218.82	21.64	0.60
ARKLAJCO	1771.09	448.18	1349.86	324.68	-421.23	0.70
ARKLAMCO	2023.46	335.88	2152.88	518.33	129.42	0.48
ARKLASCO	2582.50	784.64	2241.85	686.24	-340.65	0.79
ARKMOFCO	461.10	78.84	471.16	93.12	10.06	0.84
ARKPUECO	422.92	53.26	422.92	53.26	0.00	1
BIGLAMCO	2956.00	303.63	2956.00	303.63	0.00	1
CHICRECO	1034.97	327.47	1034.97	327.47	0.00	1
FOUPINCO	831.66	108.66	831.66	108.66	0.00	1
FOUPUECO	865.45	114.98	924.82	117.41	59.37	0.35
HUEBOOCO	2278.11	627.15	2267.58	612.57	-10.52	0.97
PURLASCO	2161.13	387.36	2161.13	387.36	0.00	1
STCHARCO	1443.38	304.15	1443.38	304.15	0.00	1
TIMSWICO	1445.61	307.38	1445.61	307.38	0.00	1

ARKJMRCO was computed using the ANN-based algorithm for the reservoir water quality transport. As anticipated during development of the ANN-based predictions (Chapter 4 – *The Simulation Challenge*), the results show that the ability of the ANN to predict measured concentrations at the reservoir outlet is affected by alterations in the explanatory variables. That is, concentrations at the reservoir inlets change as result of the inability to match the measured values during the water quality calibration. Although the explanatory variables for calibration of reservoir salt transport modeling reflected slightly different conditions than occurred historically, the ANN reservoir outlet concentration predictions followed a close trend with the measured concentrations (Figure 6.42), giving some confidence in the consistency of the predictions despite changes in system conditions. The simulation runs presented the ANN with variations in the baseline scenario (i.e., historical conditions), which dictated changes in the concentrations downstream of the reservoir. The reservoir salt transport modeling plays an important role in the analysis of the management alternatives.

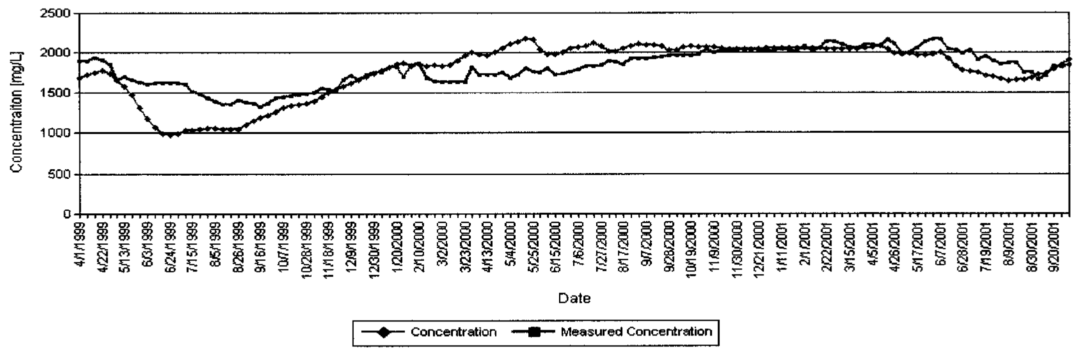


Figure 6.42 – ANN-based John Martin Reservoir water quality transport results

Deliveries based on Water Rights

During calibration, the Arkansas River modeling system allocated available flows to the demands based strictly on the specified water rights. The MODSIM consumptive demands were set to the maximum amount deliverable at each point. The water right decree amounts assigned as capacities on the links conveying flows to the nodes served to limit the amounts delivered at each time step. In this exercise, the reservoirs were set to meet historical storage levels by assigning these targets as the highest priority in the system. Storage contracts and alternate points of diversion were modeled with higher priorities than other water rights, and therefore these historical flows were preserved in the simulation. Water allocation differed from the historical records when an entitled diversion did not occur historically, which affected water available in the system for all diversions with more junior water rights. In this case, differences between the historical and calculated diversions across the basin show significant differences, exemplifying the uncertainty introduced by the human component influencing the water diversion operations. As a consequence, the consumptive water demand time series were used in the simulation to provided additional information to the water rights allocation, thereby maintaining the system operation as close as possible to the historical conditions. Further investigation of these operational uncertainties was not pursued in this study. For future work, the *LAR GeoDSS* tool can be applied to comparing strict water rights allocation with historical occurrences to further investigate the source of situations that might be causing of the differences between the expected and actual diversions.

MODEL SIMULATION

The baseline simulation network was created using the Base-Network with the same settings as the calibration network, i.e., enabling the ANN-based stream-aquifer interaction, the John Martin Reservoir salt transport modeling, and the *LAR GeoDSS* water quality module. The network simulation implemented the calibration flows and salt loadings computed during the calibration step as fixed system inflows and outflows. Simulation was carried out in two reservoir operational modes: (1) using the historical volumes in the reservoirs as storage targets, and (2) using a MODSIM reservoir layer balancing set up.

Reservoir Modeling Mode A

This modeling mode used the *LAR GeoDSS* Base-Network defaults, i.e., the reservoir historical volumes as storage targets and the priorities of 500 and 600 for Pueblo Reservoir and John Martin Reservoir respectively. As expected, these results show full agreement between the calibration and simulation flows and concentrations, demonstrating the adequate implementation of the simulation algorithm using the calibration flows and salt loadings. Pueblo and John Martin Reservoirs operated according to the specified targets in this case (Figure 6.17 and 6.18). No shortage occurred in the baseline simulation run for demands having water shortages during calibration since the baseline simulation recalculated water demands equaled the actual water supplied during calibration. For the improved water management alternatives demands were adjusted according to the characteristics of the scenario (e.g., reduction in areal recharge or reduction in seepage).

Reservoir Modeling Mode B

In this reservoir modeling mode, the reservoir storage space was divided into storage layers that store water using incremental costs assigned to each layer. The cost of the system reservoir layers were set up to fill the reservoir layers in such pattern that system storage is balanced between the reservoirs. The storage target was set to the maximum volume since the incremental costs assigned to the reservoir layers drives the allocation of water. The node priorities and layer costs were adjusted to manage the operation of the reservoirs in similar fashion to the historical operation. In this simulation mode, a calibrated network was used to provide historical flows through the control points, while using the reservoir layer to store water in the system reservoirs. The cost adjustment process showed that Pueblo Reservoir required slightly higher priority (1760) than John Martin Reservoir (1800), with the corresponding storage link cost of -32000 and -32400 respectively. Ten layers were defined for modeling both John Martin and Pueblo Reservoirs, with the layers defined as a percentage of the reservoir capacity, where John Martin Reservoir capacity was 701,755 acre-ft and Pueblo Reservoir capacity was 357,000 acre-ft. Table 6.18 shows the definition of the layers in John Martin Reservoir and the associated incremental costs. Table 6.19 gives the Pueblo Reservoir layers and costs.

The ANN prediction sensitivity was tested using this operational mode. The stream-aquifer interaction modeling was simulated for comparison with both ANNs trained as described in Chapter 4, corresponding to Datasets A and B. The Dataset_B was trained using the flows in this system operational mode. The use of the Dataset_B ANN required re-calibration of the system using historical reservoir storages and calculation of the corresponding gains and losses that match the measured flows, whereas the ANN for Dataset_A used the Mode A calibration.

Table 6.18 – John Martin Reservoir Layers Definition and Incremental Cost

Initial Volume	Ending Volume	Capacity Percent	Cost	Total Cost
0	140351	20	200	-31800
140351	210526.5	30	266	-31734
210526.5	280702	40	333	-31667
280702	350877.5	50	400	-31600
350877.5	421053	60	466	-31534
421053	491228.5	70	533	-31467
491228.5	561404	80	600	-31400
561404	631579.5	90	800	-31200
631579.5	666667.25	95	1000	-31000
666667.25	701755	100	1500	-30500

Table 6.19 – Pueblo Reservoir Layers Definition and Incremental Cost

Initial Volume	Ending Volume	Capacity Percent	Cost	Total Cost
0	71400	20	300	-32100
71400	107100	30	366	-32034
107100	142800	40	433	-31967
142800	178500	50	500	-31900
178500	214200	60	566	-31834
214200	249900	70	633	-31767
249900	285600	80	700	-31700
285600	321300	90	900	-31500
321300	339150	95	1100	-31300
339150	357000	100	1600	-30800

Using the Mode A calibration and the Dataset_A ANN, the reservoir storage as a result of this operational mode is shown in Figures 6.43 and 6.44 for Pueblo and John Martin Reservoirs, respectively. The calibration storage corresponds to the historical storage in this case, which is provided for performance comparison. This reservoirs operational mode stored larger volumes in Pueblo Reservoir, and consequently smaller volumes in John Martin Reservoir. The operation resulted in an extremely low level in John Martin Reservoir, which should be improved in the future for more realistic simulation. Since the calibrated local gains and losses were computed based on the historical measured flows, simulations for this operational mode assumed that the historical hydrological and operational conditions on which the calibrated flows were based remained unchanged in this simulation (e.g., precipitation, end of the field runoff, canal operational flows.)

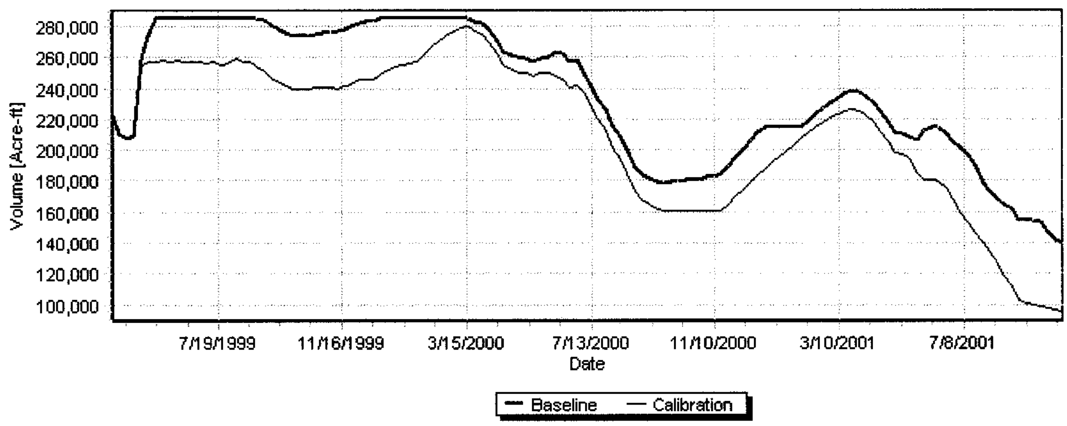


Figure 6.43 – Pueblo Reservoir storage in Mode B simulation

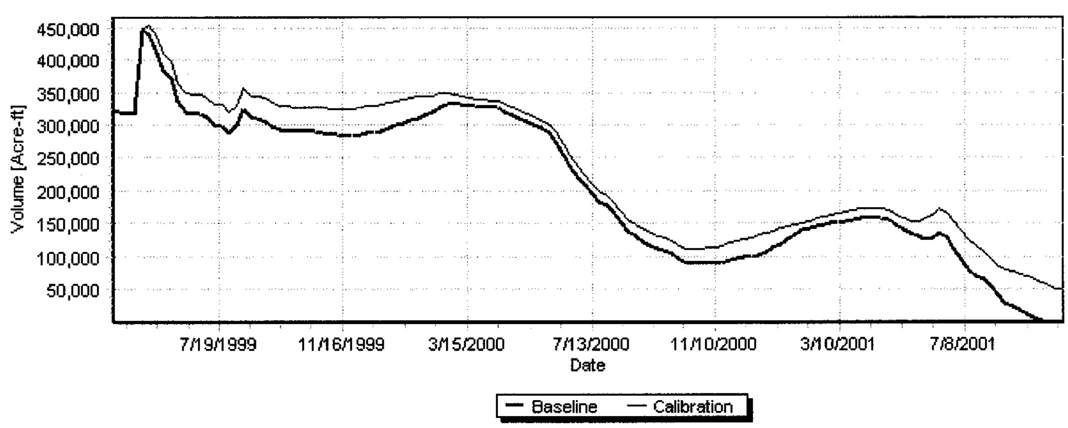


Figure 6.44 – John Martin Reservoir simulated storage in Mode B

A comparison of selected simulation indicators was carried out to verify the algorithm key elements and observe the stream-aquifer interaction sensitivity in this simulation mode to both small changes in modeling conditions and ANN training and number of recurrent variables. Table 6.20 shows a summary of selected simulation indicators for the baseline simulations in operational mode B with different ANNs for stream-aquifer simulation, as well as, the calibration network in operational mode A for comparison. Storage at the end of the simulation was the same in Mode A and Mode B with Dataset_B, indicating that the same total amount of water is stored in the system, even though, in operational mode B the reservoir storages are different than the historical. The end-of-simulation storage was lower in the Mode B with Dataset_A simulation because this network used the calibration from Mode A. In this case, the ANN generated lower net return flows, thereby causing a reduction in storage at the end of the simulation (Figures 6.43 and 6.44). The total system demands were the same in the compared runs, with zero shortages in the baseline simulation runs as expected. The baseline simulation network in Mode B, with the ANN used in Mode A, changes the way water was moved in the system. Therefore, the stream-aquifer interaction modeling explanatory variables were affected and consequently small variations in the return flows and concentrations could be observed in the results. The overall stream-aquifer interaction modeling results show a low sensitivity of less than 1%, to small variations in the MODSIM dependent explanatory variables (i.e., streamflow).

Small sensitivity was also observed in the predictions using ANN from Dataset_B in the simulation, demonstrating the consistency in the predictions generated by the priming algorithm that avoids having large errors due to accumulation of errors using recurrent variables from the *LAR GeoDSS* predicted values (Dataset_B contained a larger number of recurrent variables). The total local gains and losses decreased in the calibration for Mode B with Dataset_B with respect to calibration Mode A. A detailed summary per reach of simulation gains and losses and the percent of change from the calibration cases is presented in Table 6.21. Few calibration reaches show percent changes larger than 2%, but in general changes were a small percentage of the calibration gains and losses. Additional flows to Kansas at the Colorado-Kansas border were handled by the additional sink node connected to the Coolidge Station as discussed previously. This node collected any additional flows in the system that cannot be stored in the reservoirs. This simulation mode generated small additional flows to Kansas, most likely coming from return flows close to the border that could not be adjusted by the calibration links.

Table 6.20 – Operational modes Indicators Comparison

Stream-Aquifer Interaction ANN		Dataset_A	Dataset_B	Dataset_A
Simulation Indicator	**Units**	**Mode A**	**Mode B**	**Mode B**
End System Storage	[Acre-ft]	145182.0	145192.0	139931.0
Total Diversion	[Acre-ft]	3027545.0	3027545.0	3027545.0
Total Diversion Shortage	[Acre-ft]	0.0	0.0	0.0
Diversion Avg. Conc	[mg/L]	1271.6	1233.9	1232.6
Canal Seepage	[Acre-ft]	605509.0	536691.2	605509.0
Total Kansas Flow	[Acre-ft]	975814.0	975804.0	975804.0
Kansas Avg Conc	[mg/L]	2590.3	2539.8	2538.3
Total Return Flow	[Acre-ft]	1717562.0	1704669.0	1711713.0
Return Flow Avg Conc	[mg/L]	2768.7	2768.5	2768.5
Arkansas River Return Flow	[Acre-ft]	1148182.0	1141118.0	1144117.0
Arkansas River Ret.Flow Conc	[mg/L]	2796.0	2794.3	2796.0
Tributaries Return Flow	[Acre-ft]	569380.0	563551.0	567596.0
Tributaries RetFlow Conc	[mg/L]	2698.4	2699.1	2695.4
Total River Depletion Flow	[Acre-ft]	19654.0	25954.0	19169.0
River Depletion Avg Conc	[mg/L]	1816.1	1684.8	1801.5
Arkansas River Depletion	[Acre-ft]	4511.0	4524.0	4281.0
Arkansas River Depletion Conc	[mg/L]	1230.9	1186.4	1189.3
Tributaries Depletion	[Acre-ft]	15143.0	21430.0	14888.0
Tributaries Depletion Avg Conc	[mg/L]	1957.1	1780.2	1945.6
Total Local Losses	[Acre-ft]	1205633.0	1196815.0	1205625.0
Total Local Gains	[Acre-ft]	1939539.0	1943164.0	1939539.0
Total Calib Flow In	[Acre-ft]	2959868.0	2966962.0	2959868.0
JMR Total Mass In	[Tons]	1710820.0	1415548.0	1415909.0
JMR Total Mass Out	[Tons]	2172141.0	2142178.8	2129815.0

The Mode B (Dataset_B) water quality calibration show a slight increase in mean squared error (Figure 6.45) with respect to the calibration network (Figure 6.40). An exception is the localized RMSE increase at ARKLASCO and ARKMOFCO control points caused by a higher number of reach zero flow events in the Arkansas River that reduced the dilution effect on the contribution of salt loadings from the tributaries. Figure 6.46 shows the average simulated concentrations in Mode B (Dataset_B) as compared with the measured concentrations at the *LAR GeoDSS* control points.

Table 6.21 – Detailed Simulation Gains and Losses per Calibration Reach Mode B with Dataset_B ANN

Reach	Inflows [Acre-ff]	Losses [Acre-ft]	GW Return Flow [Acre-ft]	River Depletion [Acre-ff]	% Calibration Change	
					Inflows	Losses
ARKAVOCO	51005	89061	146730	1851	-0.01	0.19
ARKCACCO	57959	106961	138930	2360	0.15	0.25
ARKCARCO	23611	43749	142305	2343	0.21	-0.04
ARKCOOKS	54933	66780	171757	210	-0.13	0.30
ARKGRACO	24319	39690	55585	0	0.15	0.09
ARKJMRCO	42495	130141	17347	144	0.00	0.01
ARKLAJCO	33451	105973	136075	270	-10.47	-0.67
ARKLAMCO	13951	104642	174327	0	1.44	0.19
ARKLASCO	55864	35173	127066	3443	0.01	1.77
ARKMOFCO	37925	29772	5568	0	-0.01	0.01
ARKNEPCO	71218	123012	138381	3036	0.04	-0.21
ARKPUECO	1366378	0	0	0	0.00	0.00
ARKROCCO	56054	185105	257445	4502	8.28	0.57
FOUPUECO	30786	16126	0	0	0.00	0.00
PURHILCO	8062	56015	0	0	37.11	-0.29
PURLASCO	15153	1335	0	0	-12.59	13.71

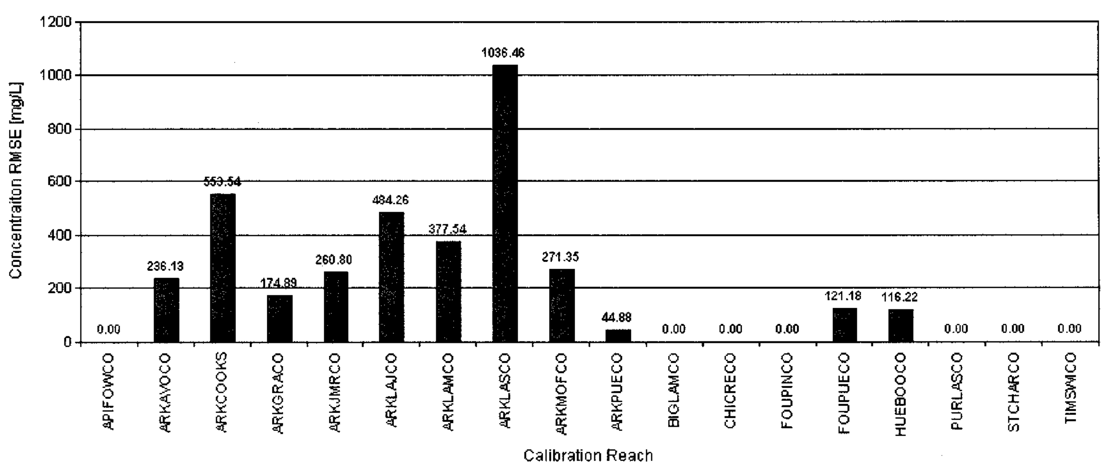


Figure 6.45 – Simulated water constituent concentration RMSE summary at the *LAR GeoDSS* control points

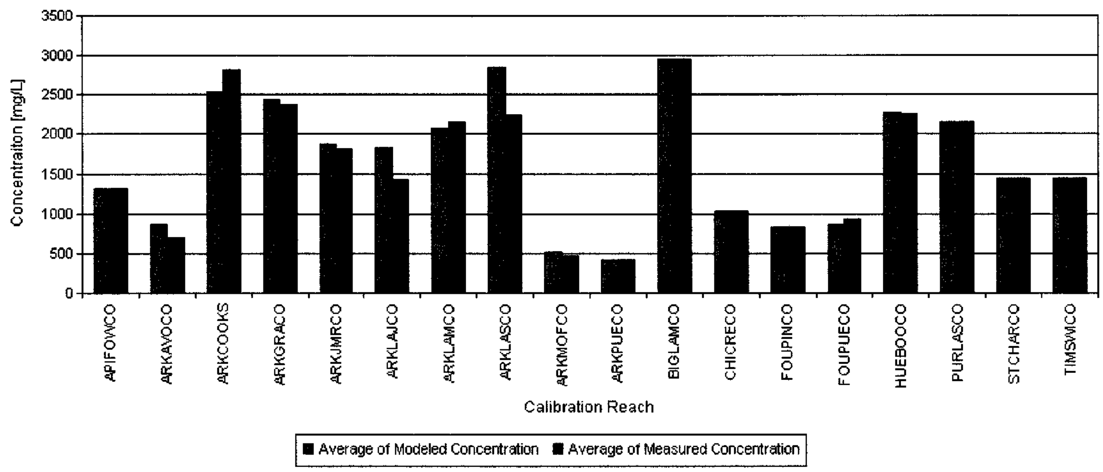


Figure 6.46 – Average concentration prediction at the *LAR GeoDSS* control points Mode B (Dataset_B)

REMARKS

Simulation of the ANN-based stream-aquifer interaction appears to closely represent the MODFLOW-MT3DMS calculated return flows and TDS concentration for the modeled reaches. However, it was found that the ANN provided gains reduced the surface water balance based gains, but at the same time, an increase in water loss. This situation suggests an over-prediction of the return flows and/or timing issues. The calibration analysis reveals a stream-aquifer interaction modeling weakness in accurately representing tributary return flows. When the sizes of the tributaries in a grouping area are significant, over predictions are expected in the smaller tributaries and under-prediction in the larger ones. In addition, it was noted that over prediction of return flows occurs in tributaries extending considerably their stream-aquifer modeled lines outside the area-buffers in the grouping area since the explanatory variables were captured only in the area-buffers that is stresses outside the area-buffers diminished since return flows per unit length of tributary are expected to reduce outside of the irrigated valley, which was not considered in the current algorithm.

The water quality calibration algorithm was unable to fully match the measured concentrations at the control points, because of the combination of inflows with unmeasured concentration magnitudes and calibration concentration limits restricted the process. The larger discrepancies are found in reaches with few or small unmeasured inflows and gains. The unmatched measured concentration occurrences propagated the calibration-calculated concentrations downstream, potentially increasing the difficulty of matching the next downstream measured concentrations. The overall water quality calibration performance show a reasonable set of modeled concentrations at the control points where, in most cases, more than 60% of the variability was explained. In the most downstream stations, the highest root mean squared error is around 500 mg/L. A small tendency to over-predict concentrations at control points where discrepancies were found indicate that there should have been more dilution in the reach that what was currently modeled.

Water allocation based solely on water rights generated discrepancies with historical diversions due to unexpected human operations of the system (e.g., not diverting entitled water), causing a cascading effect on all the more junior water users resulting in large inconsistencies basin-wide with the historical diversions. Diversion records time series are recommended to keep the water rights water allocation in track and closely simulate historical conditions.

The ANN-based stream-aquifer interaction modeling show low sensitivity to changes in average river flows, which were used extensively as explanatory variables (four previous values were used as shown in Figure 4.16). This characteristic gives confidence in the stability of predictions on small variations in the explanatory variable space.

CHAPTER 7

EVALUATION OF BASIN SCALE IMPROVED WATER MANAGEMENT ALTERNATIVES IN THE LOWER ARKANSAS RIVER VALLEY, COLORADO

The *LAR GeoDSS* is applied to screening of improved water management alternatives in the LARV in Colorado from Pueblo Reservoir to the Colorado-Kansas State Line (Figure 1.1). The ultimate goals of the management alternatives are to maximize the net economic benefits of agricultural production and to improve water quality of the stream-aquifer system by reducing salinity, waterlogging, salt loads and concentrations in the stream-aquifer system and non-beneficial consumption of water; while maintaining water right entitlements and river compact agreements. The study uses a retrospective approach in which "what if" scenarios are used to compare the flows, concentrations and system storage under various management alternatives with the historical-calibrated baseline. The purpose is to quantify the expected relative improvements to the river system that are possible by applying these various alternatives, as well as ascertaining the feasibility of implementation in a complex, legally constrained system. The management alternatives are evaluated using the conjunctive surface and groundwater quantity and quality modeling tools presented in Chapter 6. As an initial approach to the alternative screening process, it is assumed that river basin water users are fully participating in the proposed management alternatives.

For these areas in the LARV where detailed groundwater modeling is unavailable a significant challenge is presented in evaluating the improved management alternatives. Figure 4.1 shows the current groundwater modeled area used in this case study, and the projected downstream modeled area where detailed groundwater modeling will be available in the near future for testing and improvement of the stream-aquifer modeling. In the non-modeled areas, the ANN-based stream-aquifer interaction module incorporated in the *LAR GeoDSS* applies learned-relationships between basin scale-measurable explanatory variables and the regional-scale stream-aquifer MODFLOW-MT3DMS modeled interaction. This procedure provides an approximation of the return flows and salt loadings to the tributaries and river, with predictions expected to increase in uncertainty with distance from the groundwater modeled region. Since the ANN has been trained to respond to system state changes during assessment of the management alternatives, the ANN is expected to predict deviations from a baseline prediction when simulating the management alternatives regardless of the baseline prediction error. These deviations can be used to evaluate the relative benefits associated with these alternatives. In addition, the ANN accommodates predicted changes in base flows in the Arkansas River and tributaries.

As presented in Chapter 6, the Arkansas River basin water quality calibration algorithm imposes restrictions that create discrepancies between the measured and the modeled salinity concentrations. The evaluation of alternatives is based on the simulated baseline concentrations rather than the historical measured concentrations. Since calibrated concentrations are used in the simulation of management alternatives, the relative comparison of changes in concentration is used as indicator of the benefits associated with each alternative.

Results of evaluation of the improved management alternatives are based on calibrated gains and losses computed for the baseline network. Therefore, the simulation of alternatives assumes that hydrologic and operational conditions present in the historical simulation scenarios are not altered by adjustments in the system operations. Since some of the management alternatives might cause changes in these gains and losses (e.g., irrigation surface runoff or canal operational flows), errors may be introduced in using the computed gains and losses. The *LAR GeoDSS* is utilized as decision support tool to evaluate the benefits and feasibility of the regional-scale management alternatives for a historical period, and it is assumed that this retrospective approach provides a reasonable framework for evaluation of improved management alternatives by reducing the impact of calibration and simulation errors in the analysis.

Description of Improved Management Alternatives

Four remediation alternatives and various combinations of these were evaluated at the regional-scale (Burkhalter 2005, Burkhalter and Gates 2005, 2006). The alternatives include increased irrigation efficiency, reduction in canal seepage, increase in groundwater pumping (vertical drainage), and installation of sub-surface drains. At the river basin scale, these alternatives are modeled as changes in water demands at the diversion points. The challenge in modeling the alternatives in the *LAR GeoDSS* is to calculate realistic reductions in historical water demands as a consequence of the simulated changes in system operations at the regional and field scales. These simulated reductions in diversions provide additional instream flows requiring decisions on appropriate allocation. Since the historical gains and losses computed during the network calibration are implemented in each simulation as high priority system sources and sinks, the reduction in diversions becomes additional water available to the surface system that should be allocated, disposed or stored. Each improved water management scenario establishes a target for combinations of increased irrigation efficiency, seepage reduction, and additional pumping alternatives that translate into a canal diversion reduction scenario. The goal is to consistently combine the diversion reduction components associated with each alternative such that system water demands reflect the combined effects of the simulated conditions.

Canal Seepage Reduction

For this analysis, it is assumed that the majority of seepage reduction in canals conveying water to the fields takes place as a consequence of canal lining or treatment measures, with small flow reductions due to other management strategies (e.g., irrigation induced aquifer recharge reduction). In this management alternative simulation, water diverted to the canal is to be reduced by an amount equal to the simulated reduction fraction of the baseline seepage loss. When a canal is hydraulically connected to the aquifer, the MODFLOW modeled seepage amount is affected by other management alternatives since changes in water table depth at the vicinity of the canal induce changes in the computed canal seepage. In this study, however, as an initial approximation, it is assumed that there are significant changes in the amounts of canal seepage only when explicit measures to reduce seepage are specified in the management alternative.

The volume of seepage from the canals in the modeled areas can be spatially determined from the MODFLOW output, but these volumes are not available for the non-modeled canals in the basin. Based on the regional groundwater model average conveyance efficiency (E_C) of 80% (Gates et al. 2002), the average channel loss coefficient ($\bar{s}$) for all canals in the LARV was assumed as:

$$\bar{s} = 1 - E_C = 1 - 0.80 = 0.20 \quad (7.1)$$

The canal seepage amount associated with a seepage reduction management scenario (S') can be computed as a function of the baseline diversion (D), the seepage coefficient ($\bar{s}$) and the seepage reduction fraction (R_S)

$$S' = D'\bar{s}' = (D \cdot \bar{s})(1 - R_S) \quad (7.2)$$

where D' = the reduced diversion for the scenario and $\bar{s}'$ = the equivalent seepage factor for this modeled alternative that generates the expected reduced canal seepage amount (S'). Therefore, for this *LAR GeoDSS* stage, the baseline total canal seepage loss was approximated as 20% of the canal diversion.

The baseline average seepage loss coefficient ($\bar{s}$) is entered by the user in the data-model field *MOD_SeepCoef* belonging to the *Modsim_Demands* feature class. This value is used in the system simulation to calculate the baseline seepage and to reduce the seepage for the management alternatives accordingly. The calculated seepage is recorded into the MODSIM output file and is available for display though the *LAR GeoDSS* analysis tools.

Increased Irrigation Efficiency

Implementation of field-based irrigation induced aquifer recharge reduction at basin scale is based on calculations performed during the regional-scale groundwater simulation. A review of the regional-scale calculation is presented in this section along with the underlying principles for its basin scale implementation.

Regional Scale Groundwater Modeling Analysis

The regional-scale groundwater modeling approach (Gates et al. 2002, Burkhalter and Gates 2005) was analyzed to establish assumptions that adequately reflect the effects of implementing the regional-scale findings at a larger basin scale.

Irrigation Induced Aquifer Recharge Calculation

Areal aquifer recharge in the regional-scale model is calculated as a function of precipitation, groundwater pumping, crop water requirements and system irrigation efficiencies. Effective precipitation (p_e) over the modeled area is calculated as a fraction of total precipitation (p). If weekly precipitation is less than 50mm, 70% of the total precipitation is assumed to be the effective precipitation (30% surface runoff); otherwise, 50% of the total precipitation is assumed effective (50% surface runoff).

$$p_e = \left| \begin{array}{ll} 0.70p & \therefore \mathit{If}\ p < 50\,{}^{mm}/_{week} \\ 0.50p & \therefore \mathit{If}\ p \geq 50\,{}^{mm}/_{week} \end{array} \right. \tag{7.2}$$

Average Irrigation Application Efficiency

For each canal command area, the equivalent diverted (D) and pumped (P) depths per irrigated area are summarized in mm per week. The weekly required evapo-transpiration per canal command area (ET) in mm is estimated using a weighted average of the calculated evapo-transpiration of the crop. Average irrigation efficiency ($\overline{E}_I$) is calculated as the ratio of the total water required (factoring out the effective precipitation) to the total water diverted and pumped from wells.

$$\overline{E}_I = \frac{ET - p_e}{D + P} \tag{7.3}$$

As mentioned above, average conveyance efficiency ($\overline{E}_C$) for canals in the command area is assumed as 0.80. Average application efficiency ($\overline{E}_A$) accounts for only water available at the field to quantify the effectiveness in the application of the water (i.e., farmer activities). The average application efficiency is defined as:

$$\overline{E}_A = \frac{\overline{E}_I}{\overline{E}_C} \tag{7.4}$$

Application efficiency values for each field in a canal command area were generated from a truncated normal distribution with a mean equal to the average application efficiency. The minimum and maximum values of the truncated application efficiency are 0.15 and 0.85 respectively. Average application efficiency for Burkhalter and Gates (2005) modeled area located upstream of John Martin reservoir was calculated using the series of efficiencies from all the fields, replacing outliers with the maximum and minimum allowed values. The average baseline application efficiency for the modeled area was computed as 0.52.

Aquifer Recharge Amount by Field

The aquifer recharge amount was calculated for each field in the command areas. Each field was assigned a random number and the corresponding field application efficiency (e_A) was assigned to each field accordingly (from the truncated normal distribution with average $\overline{E}_A$). The required irrigation depth (h_I) per field was calculated as:

$$h_I = h_{ET} - p_e \tag{7.5}$$

where h_{ET} = total evapo-transpiration depth in the field as a function of the crop and its development stage.

The field application amount depth (h_a) was calculated for fields with positive values of h_I (i.e., when effective precipitation was smaller than the required irrigation depth) as:

$$h_a = \frac{h_I}{e_A} \tag{7.6}$$

The deep-percolation fraction (*DP*) in the regional-scale groundwater modeling was assumed as a fraction of the total irrigation loss (i.e., the applied irrigation depth in excess of the required depth). An assumed uniform DP fraction of 0.7 was used to compute the portion of excess water percolating below the root zone. This value was based on field data collected in the Colorado's South Platte River Valley (Walter 1995). The field leaching fraction (*lf*) is calculated as:

$$lf = DP(1 - e_A) \tag{7.7}$$

Based on the average field application efficiency for all canals in the regional-scale groundwater modeled area, the average leaching factor in the modeled area is adopted as:

$$lf = 0.7(1 - 0.52) = 0.34 \tag{7.8}$$

and field recharge depth (h_R) is approximated as:

$$h_R = lf(h_a + p_e) = DP(1 - e_A)\left(\frac{h_I}{e_A} + p_e\right) \tag{7.9}$$

substituting Equation 7.5 in this equation gives:

$$h_R = DP(1 - e_A)\left(\frac{h_E - p_e}{e_A} + p_e\right) \tag{7.10}$$

In terms of the water depth applied to the fields:

$$h_R = DP(1 - e_A)(d_f + p_f + p_e) \quad (7.11)$$

where d_f = proportional surface water diversion depth applied to each field and p_f = pumping equivalent depth of water applied to each field. The adjusted recharge to the groundwater table is calculated assuming irrigation scheduling and water availability for each week.

Reductions in h_R by increased irrigation efficiency not only contribute to lowering the water table, but also have an effect on the leaching of salts from the root zone to the water table (Burkhalter and Gates 2006). This effect is accounted for in the unsaturated zone module of the MODFLOW-MT3DMS model used to calibrate the ANN module.

Areal Recharge Reduction Implementation at Regional-Scale

Since the main source of areal recharge reduction is increased irrigation efficiency, aquifer recharge reduction was simulated only during the irrigation season. Modeled recharge for the improved management scenarios should not significantly change during the off season, where precipitation is the primary source of recharge. Figure 7.1 illustrates an example of the weekly total aquifer recharge for the Burkhalter and Gates (2005) modeled area as an input to MODFLOW-MT3DMS for alternative *Rech80Seep90Drain50*, which implements 80% areal recharge reduction (through increased irrigation efficiency), 90% seepage reduction and subsurface drainage with density of 50 (i.e., 50 m spacing of 2.5 m-deep sub-surface horizontal relief drains installed in fields with water table depth of less than 2.0 m).

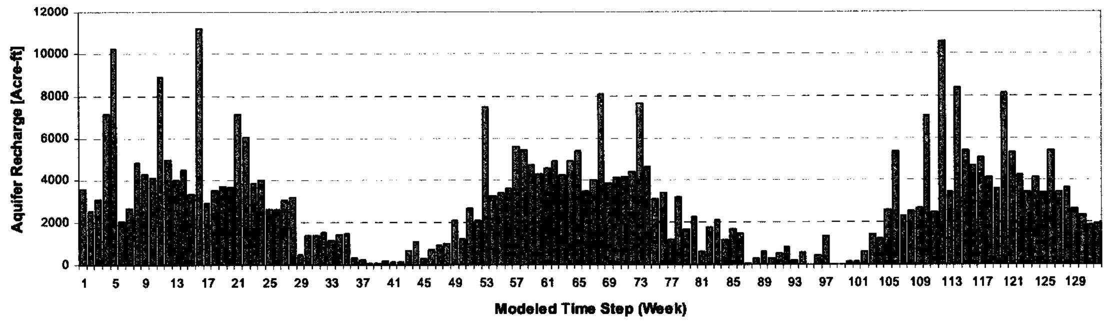


Figure 7.1 – Example of the total aquifer recharge volume simulated in MODFLOW

LAR GeoDSS Aquifer Areal Recharge Modeling

The areal aquifer recharge amount is a function of water available at the fields for irrigation. Part of the total water diverted (D) to a canal per time step seeps out while flow is conveyed to the farm delivery gates. Therefore, only a portion of the diverted water (*F*) is available to irrigate the fields, which is approximated as:

$$F = D - D \cdot \bar{s} \qquad (7.12)$$

Ultimately, areal recharge to the aquifer is a fraction of the total available water at the field, which includes delivered surface water, precipitation and pumped water. For practical purposes, recharge reduction in *LAR GeoDSS* is assumed to apply only to the delivered surface water available at the fields. Therefore, reduction of water diverted to a canal is based on the portion of the baseline areal aquifer recharge that is reduced under that canal. The fraction of *F* representing deep percolation was computed using the application efficiency and the average leaching fraction (*lf*):

$$R_d = F \cdot (lf) = F \cdot \left(DP\left(1 - \overline{E}_A\right)\right) = 0.34 \cdot F \qquad (7.13)$$

where R_d = the amount of water available at the fields that recharges the groundwater aquifer as deep percolation. Start and End dates for the irrigating season are entered by the user in the *LAR GeoDSS Simulation Scenario Manager* interface, which trigger the simulation of areal aquifer recharge reduction for those time steps that fall between them. Default dates for the irrigating season are set to April 1st to October 31st.

Pumping Increase

Additional groundwater pumping was evaluated as an alternative intervention to lower saline water table elevations where historical pumping is increased by an alternative-specified factor to simulate a vertical drainage situation. In this simulation, additional pumped water was assumed returned to the river system during the same time step using the surface drainage network. This condition was simulated in the *LAR GeoDSS* by evenly distributing the additional water pumped over all non-storage river nodes in the grouping area. Each of the non-storage river nodes was set with a local inflow equal to its corresponding fraction of the additional pumping. The concentration of the non-storage node inflow was set to the computed groundwater concentration. The amounts and concentrations were available in the *LAR GeoDSS* output display under the non-storage node local inflow.

In addition to vertical drainage, an agricultural water exchange situation was implemented in the *LAR GeoDSS* as a water use option for this scenario. In this case, the extra pumped water (ΔP) was used to irrigate crops by exchanging it for available surface water that was not diverted at the canal head gate. Therefore, the diversion to the canals was accordingly reduced in this case. Water pumped in this scenario was assumed to directly replace a portion of the surface water available to the fields (*F*). Water available to the fields in the management alternative simulation F' is calculated as:

$$F' = \left(D - D \cdot \bar{s}\right) - \Delta P \tag{7.14}$$

The percentage of pumping increase from the baseline (I_p) was entered by the user in the *LAR GeoDSS Simulation Scenario Manager* interface. For example, if a value of $I_p = 20$ is entered in the GUI, it is interpreted as a resulting pumpage of 120% of the baseline pumping.

Subsurface Drainage Improvement

This management alternative improves subsurface drainage by installing horizontal perforated pipe drainage systems at various spacings and at a uniform drain depth of 2.5 m (8.2 ft) in irrigated fields with water table depth less than 2.0 m (6.6ft). It was assumed that this scenario does not interfere with canal diversions in the system and that the irrigation water amount applied to the fields remains relatively unchanged. Subsurface drains capture groundwater flow, thereby lowering the saline water table and increasing the rates of return flow to the surface water system. Water quality is potentially improved slightly since dissolution of salts in the porous media is reduced due to transit of flows in the drains rather than through the subsurface. Volumes drained through the improved drainage system were available in the regional modeled area but unavailable every where else in the basin. An additional model would have been required to predict basin-wide drained volumes; therefore, simulations of these management alternatives in the *LAR GeoDSS* reflect only the corresponding changes in the groundwater return flows. In other words, drainage effluent was not routed back to the river in the current version of the model. As a result of this assumption, it is expected that the results of this simulation indicate the minimum improvement achieved with the implementation of subsurface drainage. An indicator was used as an ANN explanatory variable to trigger the effect of this management scenario in the ANN stream-aquifer interaction modeling.

ALTERNATIVES MODELING METHODOLOGY AND IMPLEMENTATION

The *LAR GeoDSS* modeling system manages additional water generated from the alternatives resulting in reductions in water demand. Water is managed to satisfy historical water demands adjusted by the reduced water demands within the specified reservoir operation rules. The Geo-MODSIM simulation model operates the system by storing water up to the specified target and releasing flows to meet system water demands by accommodating the operations to changes in return flow patterns and timing.

LAR GeoDSS Simulation Variables

The *LAR GeoDSS Simulation Scenario Manager* adjusts system demands and equivalent seepage coefficients to reflect the simulated management alternative. Since multiple management alternatives can be applied simultaneously, the interrelationship between them must be considered when implementing the water demand adjustments. In this section, a set of equations was developed to compute canal diversion reductions and seepage coefficients for the combined impacts of the alternatives. The most general case was the combination of three management scenarios (i.e., irrigation-induced areal recharge reduction, seepage reduction, and additional pumping). In this case, reduced volume available to the fields (F') is calculated as:

$$F' = D' - D'\bar{s}' \tag{7.15}$$

where D'= the adjusted water demand at the canal head gate and $\bar{s}'$ the adjusted average canal seepage loss coefficient. Water available to the fields for the combined recharge and pumping scenarios can be calculated as:

$$F' = F - F \cdot lf \cdot R_R - \Delta P = F \cdot (1 - lf \cdot R_R) - \Delta P \quad (7.16)$$

Substituting Equation 7.12 into Equation 7.16 and combining term gives:

$$F' = D(1-\bar{s})(1 - lf \cdot R_R) - \Delta P \quad (7.17)$$

substituting Equation 7.15 into Equation 7.17 gives:

$$D' - D'\bar{s}' = D(1-\bar{s})(1 - lf \cdot R_R) - \Delta P \quad (7.18)$$

From Equation 7.2, the simulation scenario average seepage coefficient can be expressed as:

$$\bar{s}' = \frac{D\bar{s}(1-R_S)}{D'} \quad (7.19)$$

substituting Equation 7.19 into Equation 7.18 yields:

$$D' - D'\left(\frac{D\bar{s}(1-R_S)}{D'}\right) = D' - D\bar{s}(1-R_S) = D(1-\bar{s})(1 - lf \cdot R_R) - \Delta P \quad (7.20)$$

Assuming reduced diversion D' is computed as the baseline diversion minus an adjustment term (ΔD), Equation 7.20 is written as:

$$D - \Delta D = D\bar{s}(1-R_S) + D(1-\bar{s})(1 - lf \cdot R_R) - \Delta P$$

or

$$\Delta D = D - D\bar{s}(1-R_S) - D(1-\bar{s})(1 - lf \cdot R_R) + \Delta P$$

$$= D(\bar{s}R_S + lf \cdot R_R(1-\bar{s})) + \Delta P \quad (7.21)$$

Equation 7.19 can be rewritten as:

$$\bar{s}' = \frac{D\bar{s}(1-R_S)}{D-\Delta D} = \frac{D\bar{s}(1-R_S)}{D-\Delta D} \tag{7.22}$$

substituting Equation 7.22 in Equation 7.21 gives

$$\bar{s}' = \frac{D\bar{s}(1-R_S)}{D-\left(D\left(\bar{s}R_S + lf \cdot R_R(1-\bar{s})\right)+\Delta P\right)} \tag{7.23}$$

Equations 7.21 and 7.23 calculate the canal diversion reduction and equivalent seepage coefficient as a function of the management alternative reduction coefficients and system characteristics such as seepage coefficients and irrigation application efficiency. Details on the implementation of the diversion reductions in *LAR GeoDSS* are available in Appendix VI – *Management Alternative Demand Reduction*.

Stream-Aquifer Interaction

The ANN-based stream-aquifer interaction modeling required computation of several explanatory variables as a function of the Geo-MODSIM modeling results. The simulation of various management alternatives required modification of system characteristics and operations that should be reflected in the explanatory variables for effective ANN training, and simulation. For this purpose, the ANN "development in passes" approach (introduced in Chapter 4 – *Training in Passes*) was adopted for the *LAR GeoDSS*. Initially, in the first pass, the management alternatives were simulated without explicit stream-aquifer modeling using a calibration network to provide local gains and losses based on measured flows. These initial simulations implemented water demand reductions to accurately model changes in basin conditions according to each management scenario, and two reservoir operation scenarios. The ANN training dataset was constructed using these simulation results. In the second pass, stream-aquifer interaction modeling in the *LAR GeoDSS* was based on the trained ANN using explanatory variables computed from the first pass improved water management scenarios to reduce the impact on the prediction and to improve convergence. Using the first pass Geo-MODSIM results to compute the explanatory variables assumed that the flows and demands do not change significantly between the first and second pass solutions. A more refined training dataset can be developed from the second pass simulations to further refine the ANN training. The results presented herein correspond to the third pass, since low sensitivity and small variations in flows and diversions were detected with respect to the second pass.

Reservoir Operational modes

Reservoir system operations were an important element when analyzing management alternatives according to water quality impacts. This was documented by Willey et al. (1996) while applying HEC-5Q to the Columbia River system and other large integrated reservoir systems in the U.S. The two reservoir operating modes introduced in Chapter 6 were used in this management alternatives analysis.

Reservoir operation under Mode A set the storage targets to the historical measured volumes for simulating situations where no additional storage was committed to the implementation of the management alternatives. In this case, non-diverted water can be stored only to replenish historically stored water. Otherwise, this water continued downstream and if not used in the same time step to meet water demands within Colorado, was conveyed to Kansas. Although this operational mode requires minimum adjustments in reservoir operations for implementation of management alternatives, the inability to store and release the non-diverted flow increases the risk of violating water rights decrees and failing to comply with the Arkansas River Compact agreement with Kansas when the non-diverted water made available in the same time step cannot over come the impact of changes in return flow patterns.

The Mode B reservoir operations used balancing layers or zones in the reservoir so as to satisfy the Arkansas River Compact and release water to make up for reductions in irrigation return flows. Implementation of this mode is potentially more challenging since it could require amendments to the current storage water laws, such as creating a separate account in John Martin Reservoir to store non-diverted water rather than distributing that water within the River compact accounts according to the current allocation percentages.

Management Alternative Comparison and Analysis

The simulated water management alternatives to improve the agro-ecological conditions in the basin were defined based on the previous regional-scale study (Burkhalter 2005). Table 7.1 provides a summary of the alternative names and descriptions, including a new alternative not modeled in Burkhalter (2005). These alternatives were designed to reduce soil and water salinity in order to improve crop yields in the basin, protect the lands from irreparable salinization, reduce non-beneficial water consumption on naturally-vegetated and fallow fields, and improve the water quality in the river. These alternatives include efficiency improvements at field scale, improvements to the conveyance system to reduce seepage, and groundwater pumping changes. Unfortunately, under Colorado water law, the use of the water "saved" by these improvements is limited. This analysis assumed that additional flows made available as a result of implementation of these alternatives could not be used for irrigating more land or additional crops. Water savings produced by the alternatives were not diverted by the water user and remained in the river system to support the alternative implementation. Water that was not diverted and remained in the surface system had a lower TDS concentration than that same water, had it been applied to the fields and returned later to the system through the stream-aquifer interaction process after working its way through geologic formations with potentially soluble salt deposits.

Table 7.1 – Simulated Management Alternative Summary

Alternative Name	Description
Baseline	Actual Historical Conditions
Seep70	Reduction of seepage rates by 70% over full length of all Canals
Seep50	Reduction of seepage rates by 50% over full length of all Canals
Seep90All	Reduction of seepage rates by 90% over full length of all Canals
Rech90	Reduction of recharge rates by 90%
Rech80	Reduction of recharge rates by 80%
Rech70	Reduction of recharge rates by 70%
Rech60	Reduction of recharge rates by 60%
Rech50	Reduction of recharge rates by 50%
Rech40	Reduction of recharge rates by 40%
Rech30	Reduction of recharge rates by 30%
Rech20	Reduction of recharge rates by 20%
Rech10	Reduction of recharge rates by 10%
Drain50	Installation of horizontal drains over select fields at 50 m spacing
Drain75	Installation of horizontal drains over select fields at 75 m spacing
Drain100	Installation of horizontal drains over select fields at 100 m spacing
Drain150	Installation of horizontal drains over select fields at 150 m spacing
Seep90RockyFd	Reduction of seepage rates by 90% over Rocky Ford Canal only

Alternative Name	Description
Pump200	Increase in pumping rates by 200%
Seep90Highline	Reduction of seepage rates by 90% over Highline Canal only
Seep90Otero	Reduction of seepage rates by 90% over Otero Canal only
Seep90Holbrook	Reduction of seepage rates by 90% over Holbrook Canal only
Seep90FtLyon	Reduction of seepage rates by 90% over Fort Lyon Canal only
Seep90Catlin	Reduction of seepage rates by 90% over Catlin Canal only
Seep90Lined20	Reduction of seepage rates by 90% over targeted 20% length of all Canals
Seep50Drain100	Combination of alternatives
Rech80Seep90Drain50	Combination of alternatives
Rech80Seep90	Combination of alternatives
Rech80Drain50	Combination of alternatives
Rech50Seep90	Combination of alternatives
Rech30Seep50	Combination of alternatives
Rech30Drain100	Combination of alternatives
Rech30Seep50Drain100	Combination of alternatives
Rech50Drain50	Combination of alternatives
Seep90Drain50	Combination of alternatives
Rech50Seep90Drain50	Combination of alternatives
New_Rech50Seep50	New Combination for basin-scale analysis

Criteria for Evaluation of Alternatives

Basin-scale performance of the management alternatives was evaluated based on several aspects of the simulation: (1) water allocation and shortages, (2) river water quality, (3) reservoir storage and operations, (4) stream-aquifer interaction, and (5) reservoir water quality transport.

Water Allocation and Shortages

Simulation of the management alternative is feasible if all water demands are satisfied since this implies that the solution is in compliance with Colorado water rights. The management alternative analysis checked for water shortages in the simulated results so as to insure that all water use demands were completely satisfied.

Reservoirs Storage and Operation

The reservoir storage is analyzed during the management alternative evaluation in both weekly and end-of-period fashions. Storage change with respect to the historical storage indicates alterations to the current operation policy that may be needed and also indicates potential for environmental benefits from additional storage, when water generated by the improved management alternatives stored in the reservoir is released during periods of high concentrations.

Arkansas River Compact Compliance

An additional check in the water allocation for the management alternative simulation was the water allocated to Kansas since water management alternative solutions that provided at least historical flows were assumed to comply with the Arkansas River Compact.

Stream-Aquifer Interaction

Changes in stream-aquifer interaction associated with the management alternatives are an important aspect to be analyzed since the nature of the alternatives implies changes in return flows and salt loadings. Altering historical dynamics of the aquifer requires changes in system operations to satisfy water demands and can cause shortages that need to be quantified in order to compare among alternatives and to determine their feasibility.

River Water Quality

An indicator used for analyzing the basin-wide water concentration changes due to implementation of the management alternatives is the average TDS concentration at the location of all canal diversions from the river. This average captures the overall improvement in the river water quality that is diverted for beneficial use.

John Martin Reservoir Salt Transport

Reservoir salt transport is an important component of the management alternative analysis since it interrupts the sequential calculation of TDS concentration in the river basin by using a prediction of the complex processes occurring in John Martin Reservoir. The prediction of concentration at the reservoir outlet dictates starting concentrations for a second set of sequential calculations in the lower part of the modeled basin. The transport analysis strategy computes a transport coefficient (T_r) as:

$$T_r = \frac{\sum Mass_{out}}{\sum Mass_{in}} \tag{7.24}$$

where $Mass_{out}$ = salt mass leaving the reservoir and $Mass_{in}$= salt mass entering the reservoir. This factor indicates an overall concentration/dilution process of flows passing through the reservoir. Based on the baseline simulation indicators (Table 6.20), the transport coefficient in reservoir operations under Mode A (historical) = 1.27, which indicates an overall solute concentration increase through the reservoir. For reservoir operations under Mode B, changes in the system operation and corresponding water quantity and quality calibration increased T_r to 1.50 in this baseline simulation. In this case, changes in the inflow time sequence and the Arkansas River inflow concentration created a prediction with higher salt loadings in the reservoir release.

Alternatives Performance Comparison

The *LAR GeoDSS Simulation Scenario Analysis* tool was used to process the results of the alternatives to compare performance by using the aforementioned analysis criteria. The summary and analysis was categorized by reservoir operational mode, with analysis of overall performance evaluated using total simulated amounts and average concentrations. Detail system performance per time step is available in Appendix VI – *Management Alternatives Detailed Analysis*.

Reservoir Operational Mode A

Water Allocation and Shortages for Operational Mode A

The satisfaction of water demands was the first aspect of the management alternatives to be analyzed. The water demands were reduced from the historical diversions to reflect the calculated impact of the various management alternative characteristics as presented in the section *LAR GeoDSS Simulation Variables*. Figure 7.2 shows the computed-total water demand and the corresponding total canal loss for the simulated alternatives, which was a function of the water diverted. The alternatives are sorted in descending order of total water demand.

Demand shortages occurred when the management alternative produced less available water to the system for satisfying the adjusted demands. These shortages in the simulated alternatives indicate that there was insufficient available water in the system to meet water demands. Shortages occurred due to reduced return flows computed in the stream-aquifer interaction modeling and due to exhaustion of storage water and non-diverted water. Figure 7.3 shows the total simulated water shortages for the management alternatives. No water shortages were necessary to guarantee the appropriate water rights allocation.

Therefore, failing to provide the computed water demands made the alternative infeasible under the current reservoir operational mode. Small shortages were revealed in many alternatives, indicating only minor violations to the water rights. Only *Pump200*, *Seep90Catlin*, *Seep90Highline* and *Seep90FtLyon* alternatives had no water shortages. At this stage in the analysis, alternatives with significant shortages were discarded since their implementation was considered infeasible. Table 7.2 lists the infeasible alternatives due significant shortages resulting in violation of the users' water rights.

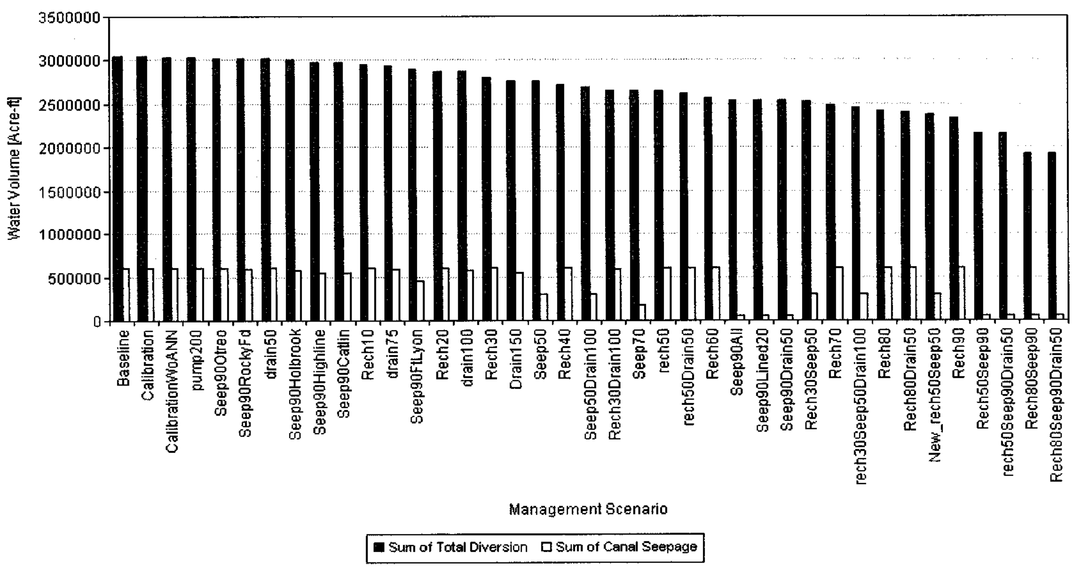


Figure 7.2 – Management alternatives water demands and canal loss for operational mode A

Table 7.2 – Infeasible Management Alternatives Due to Water Shortages in Operational mode A

Alternative Name	Water Shortage [Acre-ft]
Drain50	13269
Rech50Drain50	36978
Rech80Drain50	41278
Seep50Drain100	72202
Drain75	89013
Rech30Seep50Drain100	89265
Drain100	154491
Rech30Drain100	155780
Drain150	268037

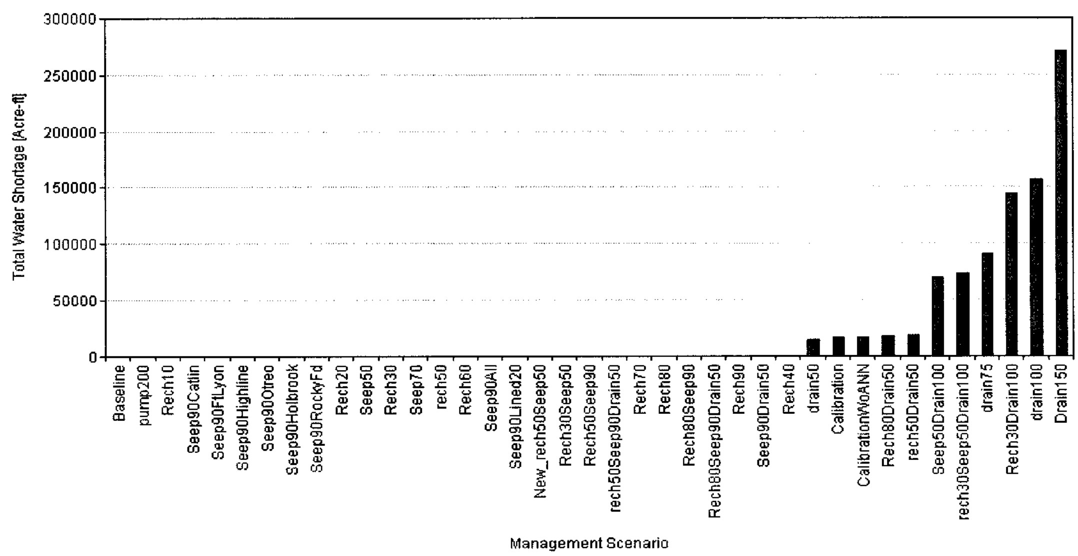


Figure 7.3 – Management alternatives water demand shortage for operational mode A

<u>Reservoir Storage and Operation for Operational Mode A</u>

In this reservoir operational mode, the additional downstream river flows caused by the alternatives were used to replace reductions in return flows and to replenish reservoir volumes to historical levels. The ability to replenish reservoir storage and maintain the system end-of-simulation storage was an indicator of the sustainability of the alternative over the long run. The modeling system in this mode used historically stored water to meet water obligations, but it was set up to recover the water as soon as possible. During simulation, a reservoir storage that was lower than the historical storage volume indicates that additional water was requested and "borrowed" from the reservoirs (see detailed plots of results in Appendix VI). The length and magnitude of the "borrowing" water operation was an indicator of the relative degree of change of the current reservoir operational polices for a successful alternative implementation.

The reservoir storage was summarized for the simulated alternatives as the end-of-simulation system storage, which can be checked against the baseline end-of-simulation system storage (Figure 7.4). Even though this operational mode was restrictive in the use of additional storage, the lack of storage at the end of the simulation represents a situation that most likely will cause difficulties in the implementation of the alternative under this system operational mode. The closer the operation is to the historical volumes, the less alteration to the current reservoir operation is required for implementation of the alternative. Under the highly constraining water laws in the LARV, requiring less modification to the current operation facilitates implementation of the alternative. Alternatives with no end-of-simulation storage were the same ones that exhibit significant shortages (Table 7.2). Ideally, storage at the end of the simulation should be the same as its counterpart in the baseline simulation to indicate that in the long run no special reservoir operation is necessary for implementation of the alternative. Alternatives with end-of-simulation storage lower than historical indicate that the alternative implementation might still be possible if additional storage is allowed.

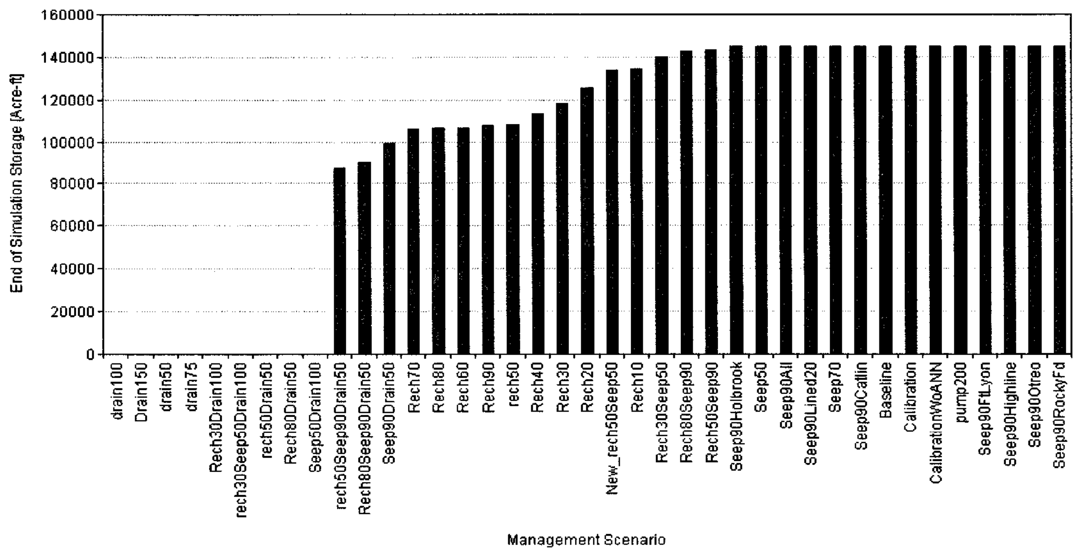


Figure 7.4 – Management alternatives end-of-simulation system storage in operational mode A

Arkansas River Compact Compliance for Operational Mode A

Management alternatives were required to at least duplicate the baseline historical flows to the Kansas account of the Arkansas River Compact, thereby assuring compliance with the Arkansas River Compact. It was assumed that Colorado was in compliance with the compact during the period 1999-2001 selected for the simulation of the alternatives. Colorado water users (Water District 67) that received water from the compact were assumed to participate in the management alternative program. Therefore, they were assumed to allow the non-diverted water to be used in the alternative implementation according to the reservoir operational mode. Figure 7.5 shows the simulated flows to Kansas for each of the management alternatives. Five alternatives failed to provide the water requirements to Kansas, including: *Drain150*, *Rech30Drain100*, *Drain100*, *Rech30Seep50Drain100*, and *Seep50Drain100*.

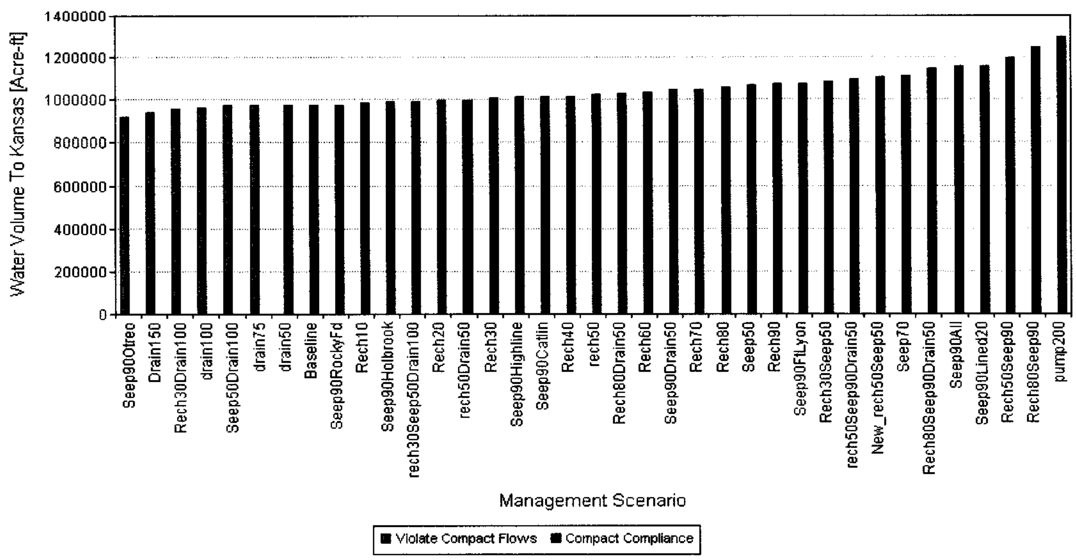


Figure 7.5 – Colorado-Kansas state line simulated flow in operational mode A for considered Management Alternatives

Stream-Aquifer Interaction for Operational Mode A

The basin-wide stream-aquifer interaction modeling performance is evaluated to provide an idea of the role in the comparative evaluation of alternatives. Basin-wide *LAR GeoDSS* predictions are presented to illustrate the behavior of the stream-aquifer interaction outside of the groundwater modeled area. The ANN-based predictions are analyzed for both the main stem and the tributaries.

Analysis in the Groundwater Modeled Area

In the groundwater MODFLOW-MT3DMS modeled area, the *LAR GeoDSS* prediction is compared against the MODFLOW-MT3DMS modeling. The regional-scale performance of the ANN predictions is analyzed using the net return flow averaged over the simulated period and over the six modeled grouping areas (i.e., 6, 7, 8, 9, 10, and 11) (Figure 4.2). Although smaller scale comparison is possible (e.g., by grouping area), it is believed that regional comparison is more descriptive of the performance in analyzing water management alternatives at the basin scale. Larger variability in the results is expected when comparing results per grouping areas, with ones results for some grouping areas better representing the MODFLOW-MT3DMS modeled values than others. Only a portion of grouping areas 6 and 11 are modeled in MODFLOW-MT3DMS; therefore, the volumetric result should consider the discrepancy inherited from the difference in the size of the modeled areas. The net return flow is computed for each time step in each grouping area as the Arkansas River accessions minus the depletions.

Return Flows Analysis

For the main stem, ANN-based net return flow and concentration prediction comparisons include all grouping areas modeled in MODFLOW-MT3DMS. Figure 7.6 shows weekly average net return flow comparison between MODFLOW-MT3DMS and the *LAR GeoDSS*, where the trend of return flow change is observed and a reduction in return flows is the most common result in both MODFLOW-MT3DMS and *LAR GeoDSS* simulation. In general, results show agreement in changes of return flow during simulation of the management alternatives with larger under predictions of return flows than over predictions, more often in management scenarios including drainage improvements. For each of the alternatives, Figure 7.7 shows the relative standard deviation or coefficient of variation (CV) over time and over grouping areas of the computed net return flow. The CV calculations reveal a larger spread of the results relative to the mean in the MODFLOW-MT3DMS predicted values than in the *LAR GeoDSS* predicted values.

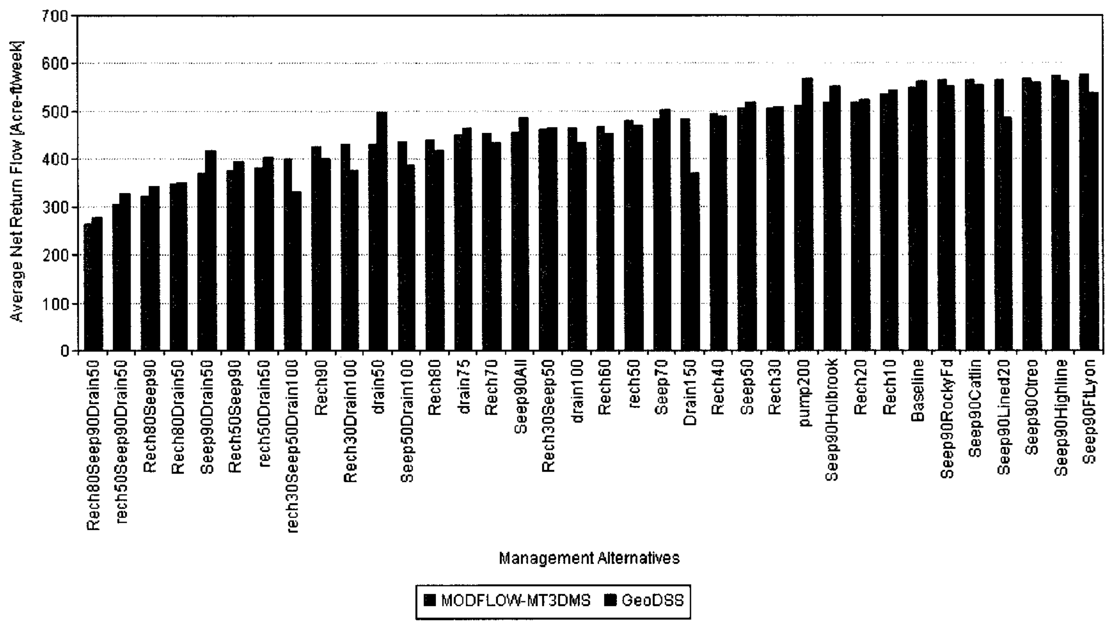


Figure 7.6 – Arkansas River average net return flow within the MODFLOW-MT3DMS modeled region for considered management alternatives

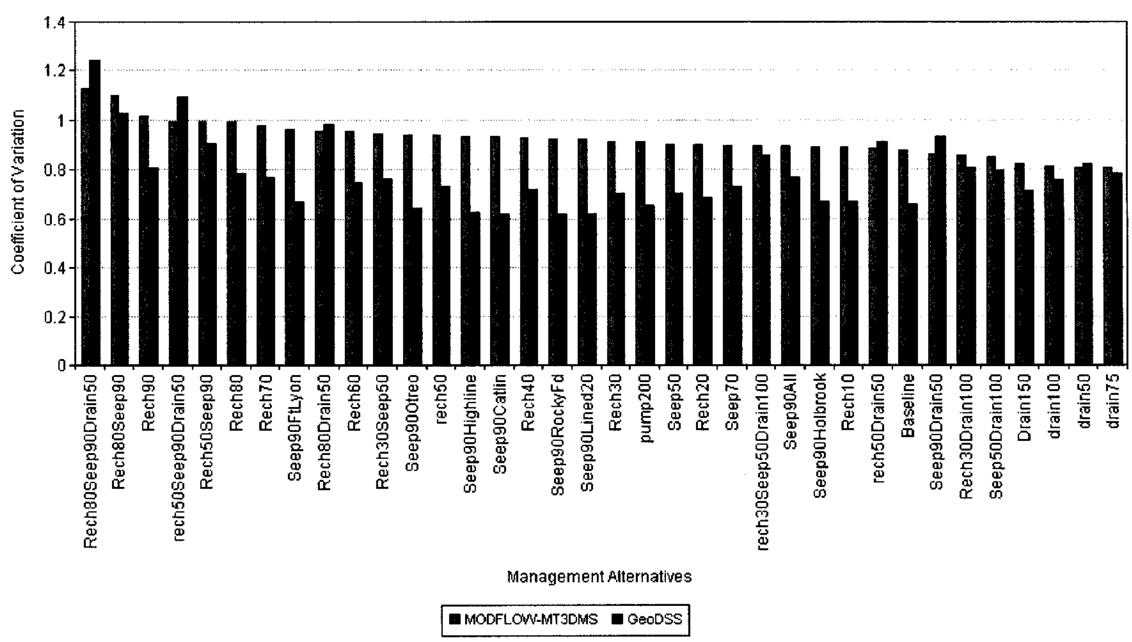


Figure 7.7 – Coefficient of variation of the Arkansas River net return flow within the MODFLOW-MT3DMS modeled region for considered management alternatives

The *LAR GeoDSS* average net return flow predictions for the tributaries in the MODFLOW-MT3DMS modeled region are compared in Figure 7.8. Contrary to the behavior observed in the Arkansas River return flow analysis, there is a clear tendency for larger over predictions of return flow in drainage improvement scenarios. It is likely that this is due to the smaller alterations to explanatory variables in the drainage improvements scenarios compared with other scenarios (only the drainage intensity explanatory variable is directly changed from the baseline). Further improvements to the ANN prediction of drainage improvement scenarios should consider the development of explanatory variables that can capture the effect of the return of additional drained water to the river system.

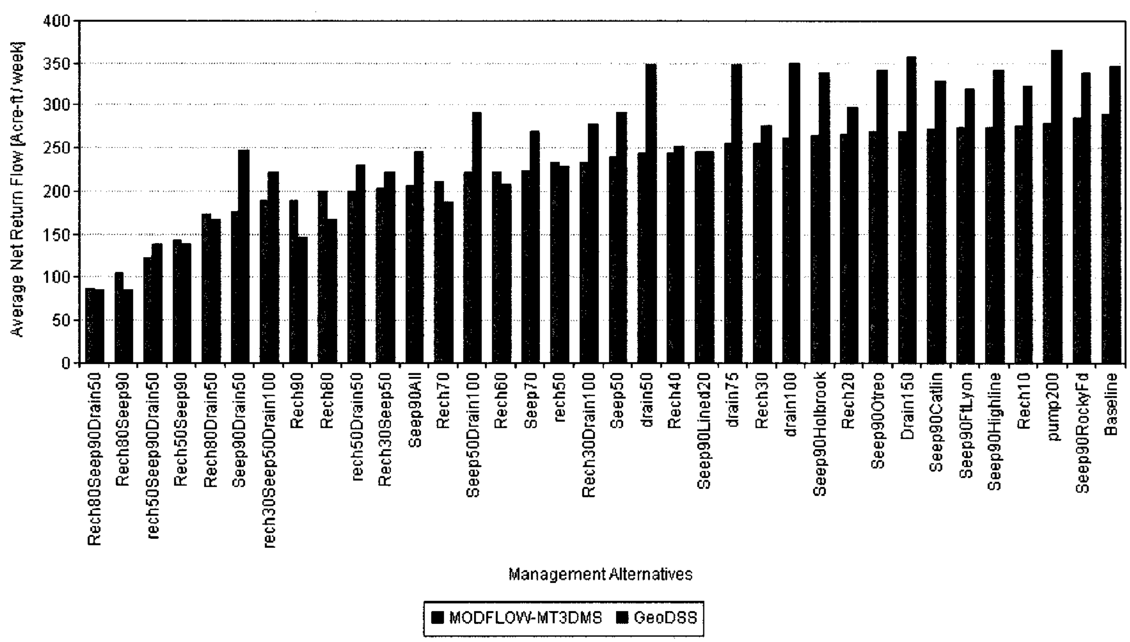


Figure 7.8 – Tributaries average net return flow within the MODFLOW-MT3DMS modeled region for considered management alternatives

The CV values for the tributaries return flow predictions are shown in Figure 7.9. Spread of both the MODFLOW-MT3DMS modeled and *LAR GeoDSS* predicted values for the tributaries are larger than the spread in the Arkansas River values. The increase of spread between the Arkansas River and tributaries return flows is well represented by the *LAR GeoDSS* predictions.

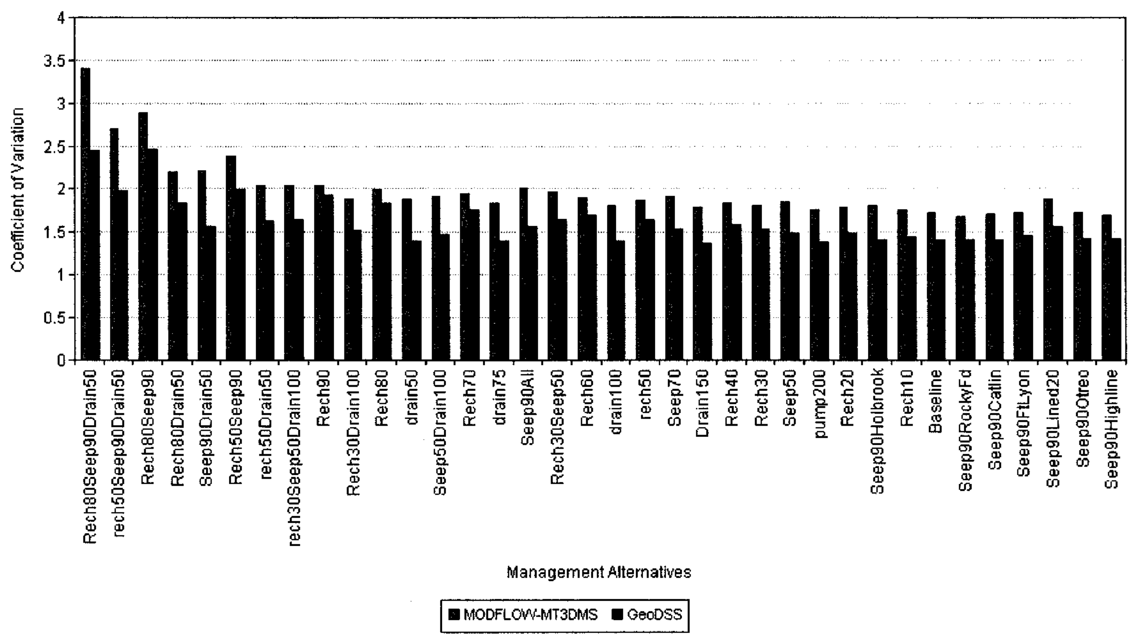


Figure 7.9 – Coefficient of variation of the tributaries net return flow within the MODFLOW-MT3DMS modeled region for considered management altenatives

The average error in the weekly return flow prediction is measured using the root mean squared error (RMSE). The RMSE for each of the management alternatives is shown in Figure 7.10. Even though average return flows to the tributaries are smaller than return flows to the Arkansas the RMSE of both predictions are in the same range, indicating a relatively larger error in the prediction of the tributary return flow. The maximum RMSE for the tributaries return flow prediction was found in the *Pump200* scenario. The RMSE for the Arkansas River return flow prediction is more uniform with relatively larger errors among alternatives with combined seepage, drainage and recharge alternatives; seepage improvements for individual canals; and drainage only alternatives.

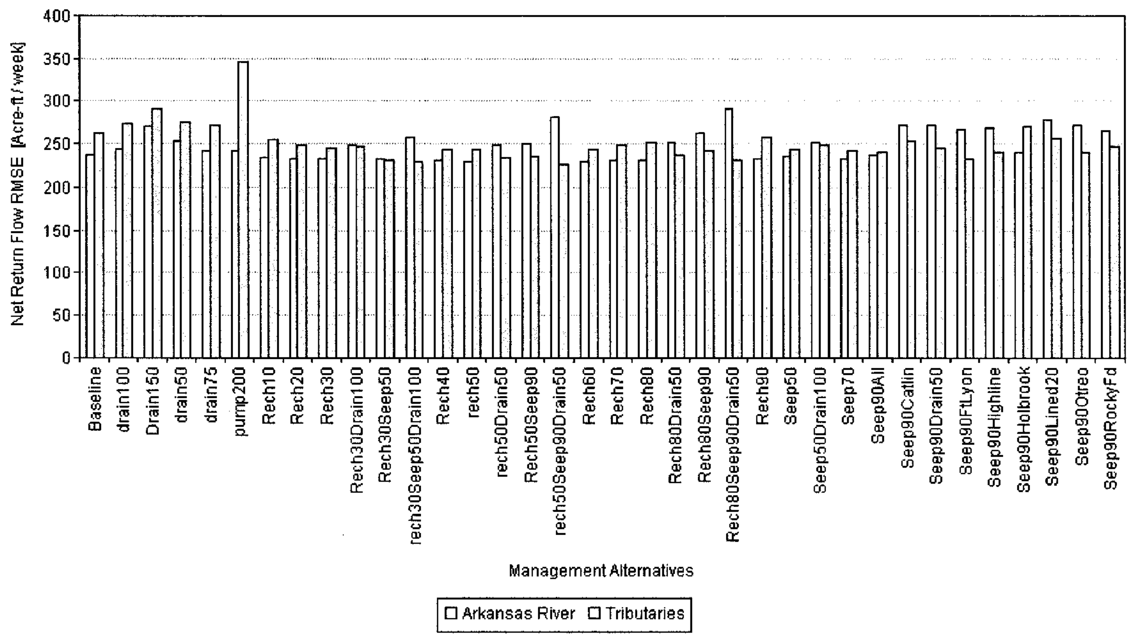


Figure 7.10 – RMSE of the net return flow prediction relative to the baseline for the Arkansas River within the MODFLOW-MT3DMS modeled region for considered management alternatives

Water Quality Analysis

Rather than analyzing the ANN-predicted return-flow concentration for the water management alternative simulations, it is more significant to analyze the salt load to the river from the groundwater, calculated as the product of the predicted return flow and concentration. This analysis allows observing changes in salt loadings to the surface system due to implementation of the water management alternatives. Figure 7.11 shows the average predicted weekly salt load to the Arkansas River. Results show under-prediction of the salt load for all the alternatives. Consistent under-prediction in salt concentration is the main reason for the under-estimation of salt loads. Special consideration should be given in interpreting these results because of the way the *LAR GeoDSS* output is generated. For cases where the ANN predicts a net depletion from a grouping area, the computed *LAR GeoDSS* salt load will be zero for this grouping area while it is computed at individual MODFLOW-MT3DMS return flow cells within the grouping area for the groundwater modeling summary. Although net depletions are not a common occurrence in this system, these cases of zero salt loading lower the computed *LAR GeoDSS* average salt load during the simulated period. The CV of the computed salt load to the Arkansas River in the groundwater modeled area is shown in Figure 7.12. Larger variability in the CV values is observable in *LAR GeoDSS* prediction. This is attributed to the combination of errors of individual predictions of flow and concentration that are used to calculate the salt load.

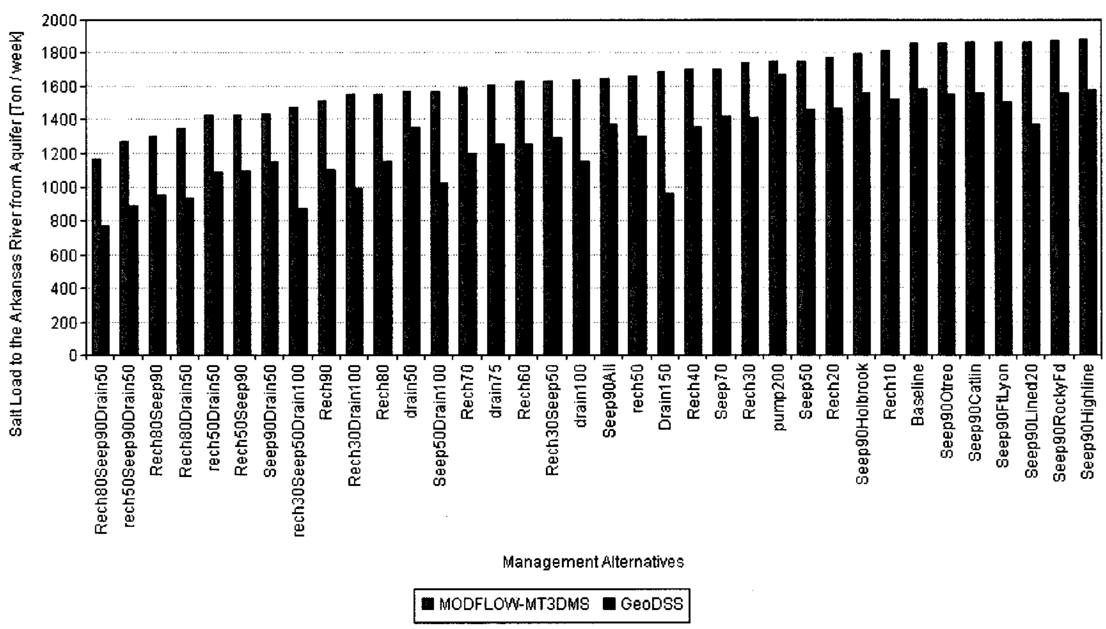


Figure 7.11 – Arkansas River average salt load within the MODFLOW-MT3DMS modeled region for considered management alternatives

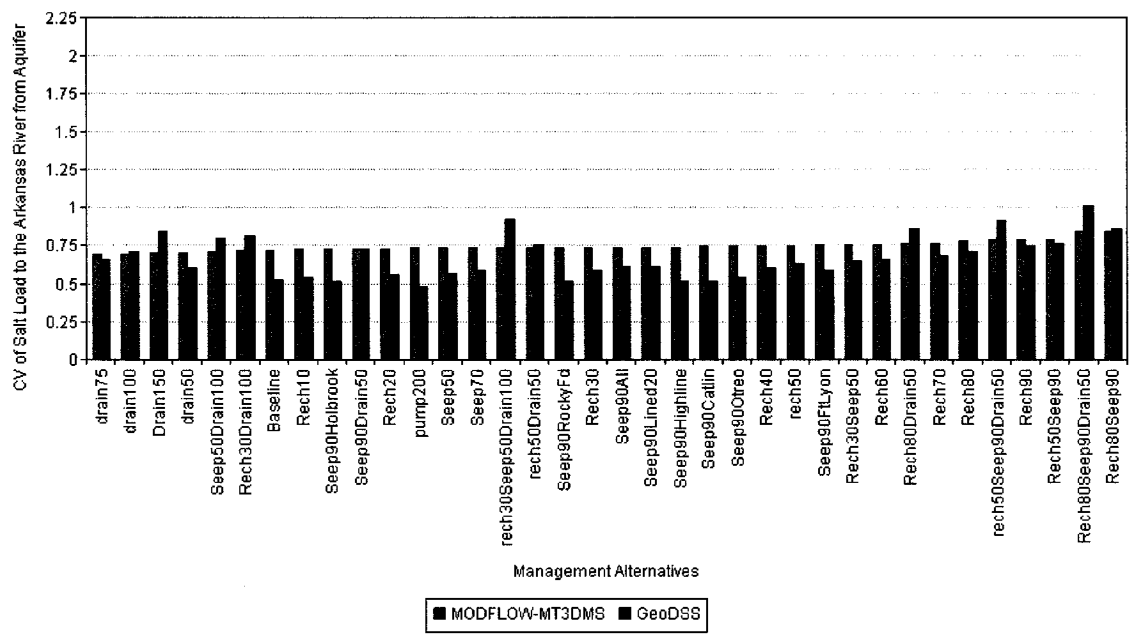


Figure 7.12 – Coefficient of variation of the Arkansas River salt load within the MODFLOW-MT3DMS modeled region for considered management alternatives

Salt load to the tributaries as the product of the predicted return flow rates and concentration is compared in Figure 7.13. Results show a total salt load to the tributaries smaller than the salt load returned to the Arkansas River. Over-prediction of the salt load is observed for management alternatives with only drainage improvements and only seepage improvements, and under-prediction occurs for alternatives with large reductions in areal recharge and canal seepage. The CV of the salt load to the tributaries is presented in Figure 7.14. In general, larger spreads are recognized in the tributaries salt load relative to the corresponding calculated values for the Arkansas River. The *LAR GeoDSS* predictions capture well the relative spreads with respect to the mean of the modeled values.

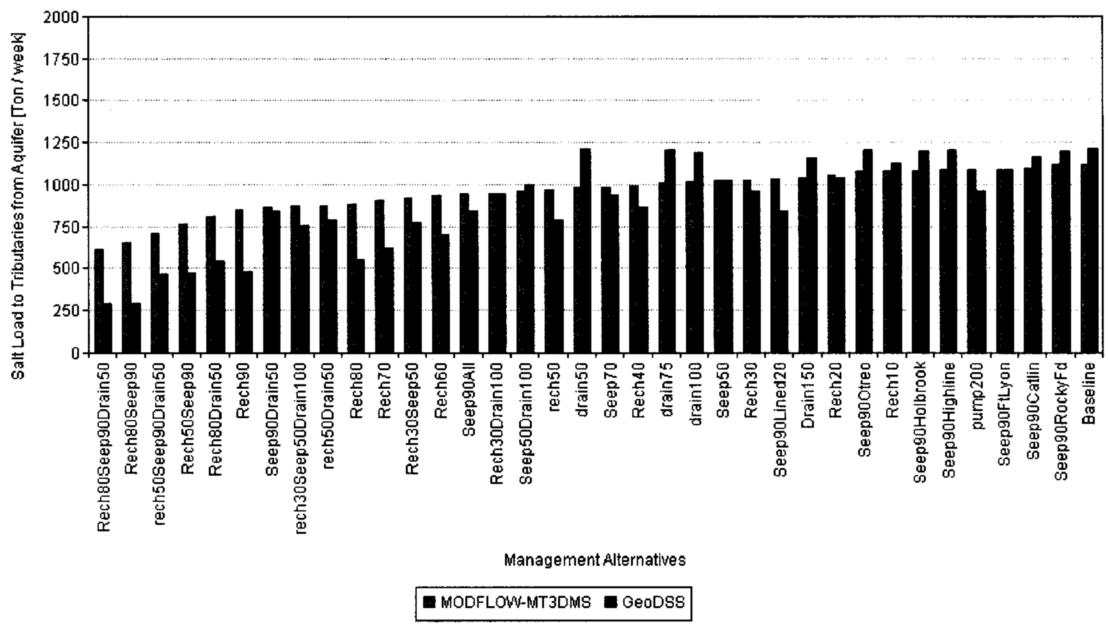


Figure 7.13 – Tributaries average salt load within the MODFLOW-MT3DMS modeled region for considered management alternatives

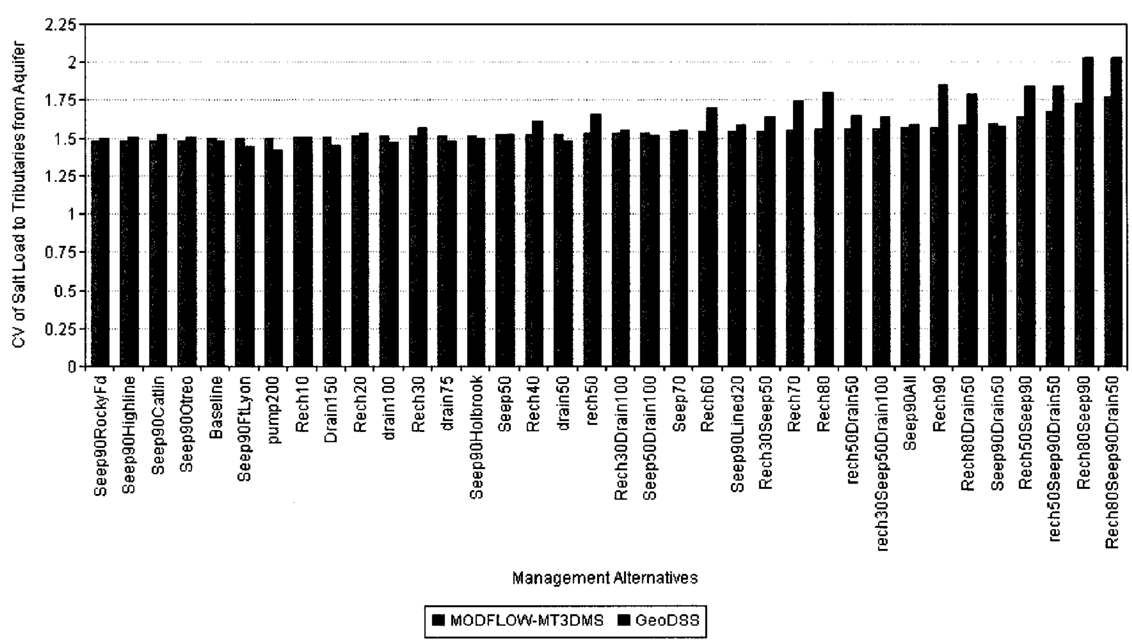


Figure 7.14 – Coefficient of variation of the Tributaries salt load within the MODFLOW-MT3DMS modeled region for considered management alternatives

The error in the prediction of average salt loads to the tributaries is summarized for each alternative using the RMSE (Figure 7.15). The magnitude and the variability of the prediction of salt loads are larger for the tributaries than for the Arkansas River. The wider relative spread identified for the tributary modeled concentration could influence the larger salt loadings errors. The MODFLOW-MT3DMS modeled tributary return flow concentrations have a higher variability than the modeled concentrations of the Arkansas River return flow, which could facilitate the ANN prediction of the concentrations for the main stem and consequently reduce the river salt load RMSE compared to the tributaries salt load RMSE.

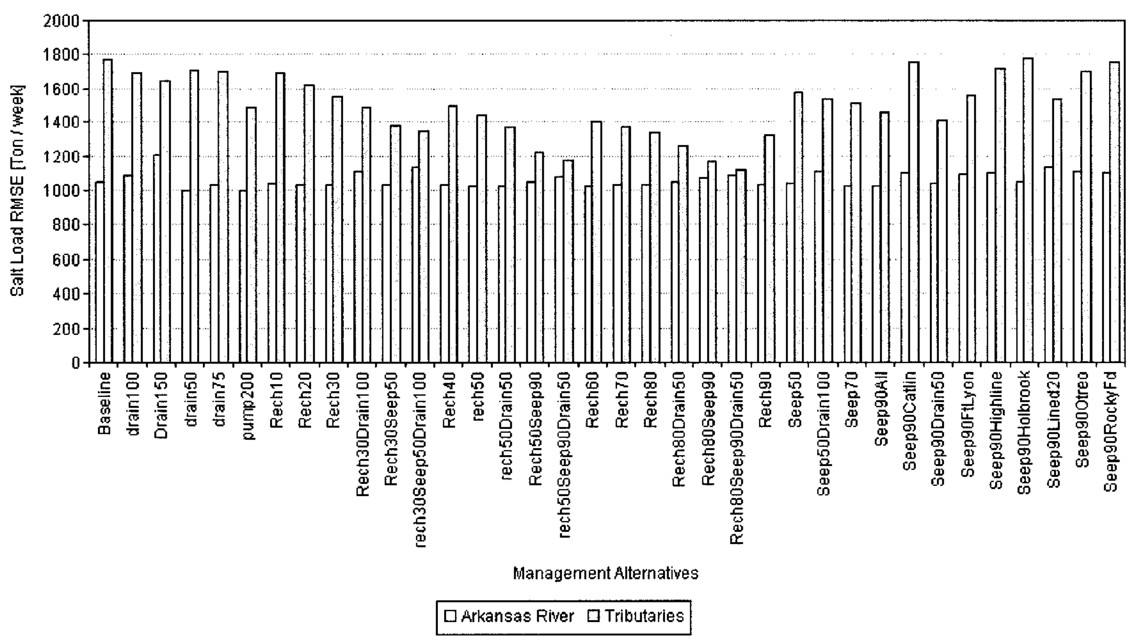


Figure 7.15 – RMSE of the salt load prediction for the Arkansas River and the tributaries within the MODFLOW-MT3DMS modeled region for considered management alternatives

Comparison of Predicted Changes Relative to the Baseline

Comparison of the change of predicted return flows relative to the baseline return flows reflects the relative ability of the ANN–based prediction to represent MODFLOW-MT3DMS simulated changes in stream-aquifer interaction for water management alternatives. Although comparing predictions relative to a predicted baseline value that itself has errors associated with it can be misleading, it is believed that this analysis provides a framework for the relative comparison and analysis of water management alternatives. Figure 7.16 shows the average change in net return flow from the baseline return flow for the Arkansas River in the MODFLOW-MT3DMS modeled area. *LAR GeoDSS* water management alternatives with larger predicted negative change than the corresponding MODFLOW-MT3DMS predicted change (e.g., Drain 150) indicate a larger return flow reduction predicted by the *LAR GeoDSS.* For all the considered alternatives, the MODFLOW-MT3DMS modeled change of return flows from the baseline averages -81.9 acre-ft/week (-101.0 x 10^3/week), ranging from -171.5 acre-ft/week (-211.5 x 10^3/week) to 816.6 acre-ft/week (1006.5 x 10^3/week). Figure 7.17 shows the comparison of the average changes from the baseline of return flows to the Arkansas River, with each point representing a management alternative average change in both MODFLOW-MT3DMS and the *LAR GeoDSS.* The points follow a linear trend with slope lower than 45°, indicating larger over-prediction of the change for larger MODFLOW-MT3DMS modeled changes. The coefficient of determination of the fitted line is 0.79. For all the water management alternatives, the RMSE of the change of return flow predicted by the *LAR GeoDSS* and the corresponding change modeled by MODFLOW-MT3DMS averages 109.3 acre-ft/week (134.4 x 10^3 m^3/week), ranging from 258.6 acre-ft/week (318.9 x 10^3 m^3/week) to 15.13 acre-ft/week (18.6 x 10^3 m^3/week).

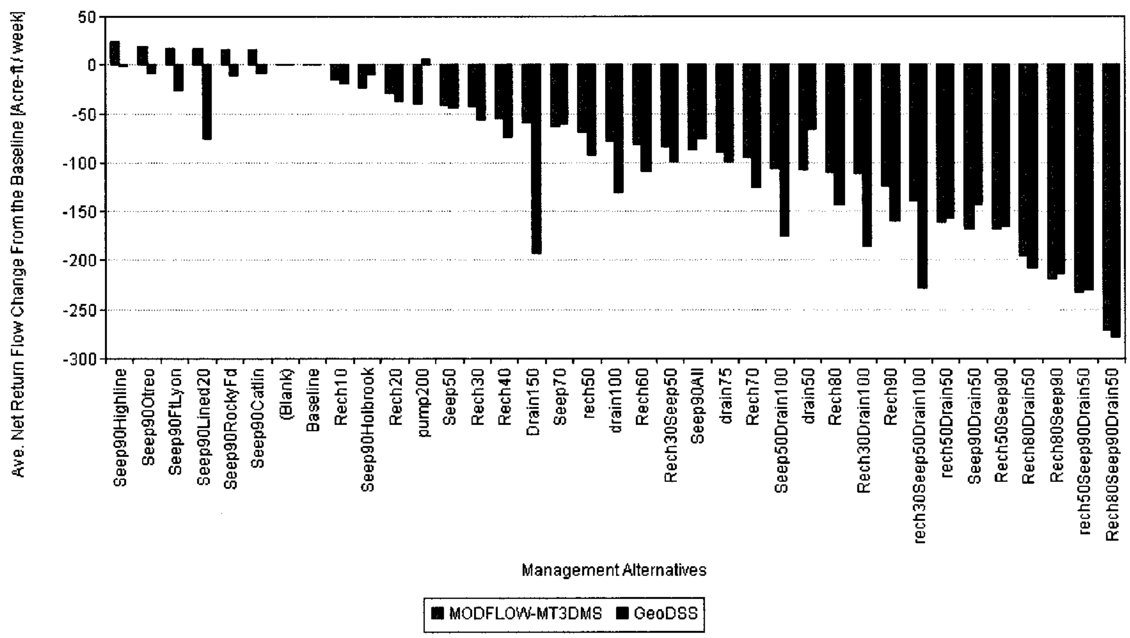


Figure 7.16 – Net return flow prediction change relative to the baseline for the Arkansas River within the MODFLOW-MT3DMS modeled region for considered management alternatives

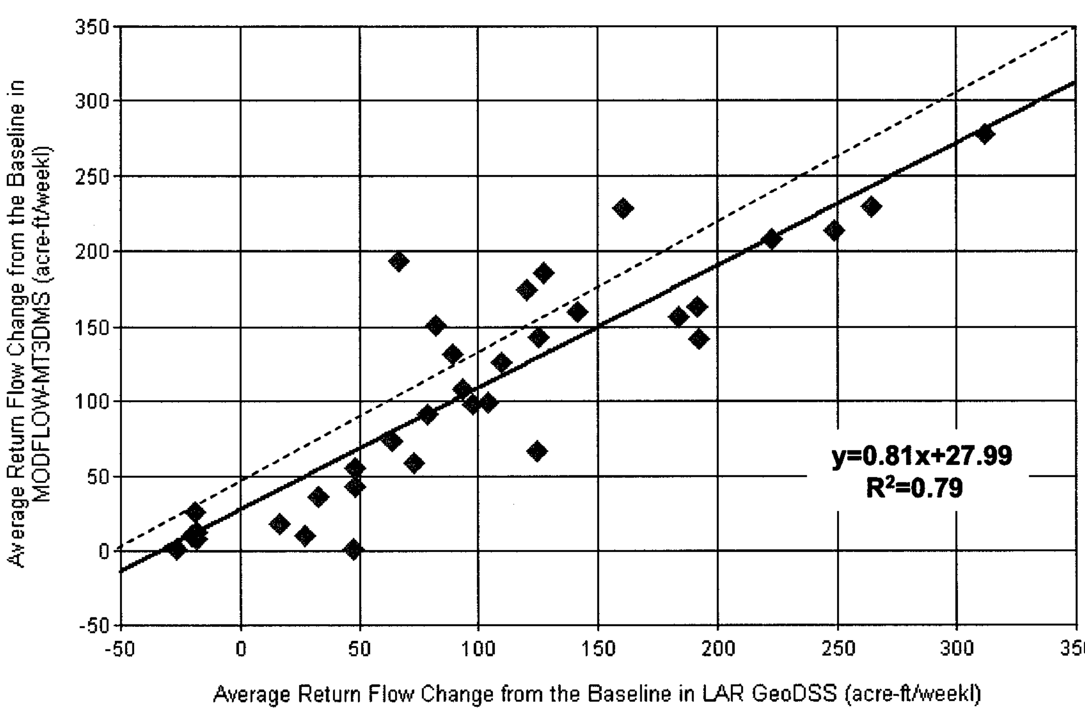


Figure 7.17 – Comparison of the average change from the baseline of return flow to the Arkansas River for considered management alternatives

The trend of the changes from the baseline suggests that a large fraction of the differences shown in Figure 7.16 can be attributed to localized larger errors rather than to generally biased predictions. Analysis of the CV of changes in return flow from the baseline is difficult to interpret due to the relatively small average change for some of the alternatives resulting in large CV values. The results show large CV values for both the *LAR GeoDSS*-predicted and the MODFLOW-MT3DMS modeled alternatives but not necessarily with the same magnitude and sign. Contrary to the findings regarding errors in the average return flow predictions, the larger CV differences (e.g., -12.5 for *Seep90Highline* scenario and 5 for *Seep90FortLyon* Scenario) could not be associated with a particular grouping area; therefore, discrepancies in relative spreads of predicted and modeled change from the baseline is found across all alternatives and grouping areas.

MODFLOW-MT3DMS modeled alternatives showing small positive change, indicating an increase of the return flow relative to the baseline, correspond to alternatives with localized improvements. Although the ANN explanatory variables can capture changes in the system stresses due to the improvements, it is believed that the differences observed in the results are a consequence of localized effects in the groundwater model that cannot be captured well in the generalized ANN prediction. The same reasoning of localized effect could apply for the single pumping scenario.

Figure 7.18 shows the average change of return flow predictions from the baseline for both the *LAR GeoDSS* and MODFLOW-MT3DMS modeled values in the tributaries. In this case, there is a consistently larger reduction of return flow in the areal recharge reduction scenarios modeled by the *LAR GeoDSS*, and a consistently smaller reduction of return flows in the drainage improvement scenarios. These comparative differences in predictions can result from the difficulty in predicting highly localized tributary return flow changes using explanatory variables that are defined for grouping areas that capture regional changes in system stresses. For all the considered alternatives, the MODFLOW-MT3DMS modeled change of return flows to the tributaries from the baseline averages -66.2 acre-ft/week (-81.65 x 10^3 m^3/week), ranging from 202.5 acre-ft/week (249.7 x 10^3 m^3/week) to 4.0 acre-ft/week (4.9 x 10^3 m^3/week). The average RMSE of change of return flow from the baseline predicted by the *LAR GeoDSS* and MODFLOW-MT3DMS is 60.0 acre-ft/week (74.0 x 10^3 m^3/week), ranging from 132.0 acre-ft/week (162.8 x 10^3 m^3/week) to 8.0 acre-ft/week (9.8 x 10^3 m^3/week)

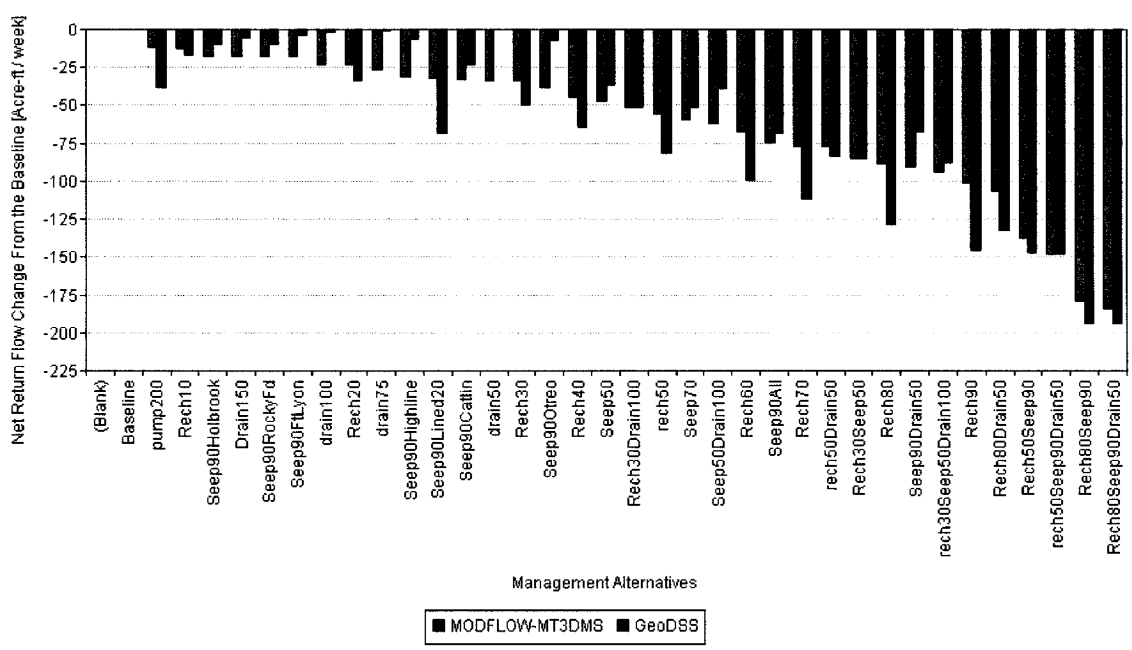


Figure 7.18 – Net return flow prediction change relative to the baseline for the tributaries within the MODFLOW-MT3DMS modeled region for considered management alternatives

The comparison of the average changes for each of the alternatives between the MODFLOW-MT3DMS modeled and the LAR GeoDSS is shown in Figure 7.19. The points representing each alternative are fitted to a linear function indicating a trend that under-predicts changes for larger MODFLOW-MT3DMS changes and represents fairly well small changes, except for the localized improvement alternatives with average negative changes modeled in MODFLOW-MT3DMS.

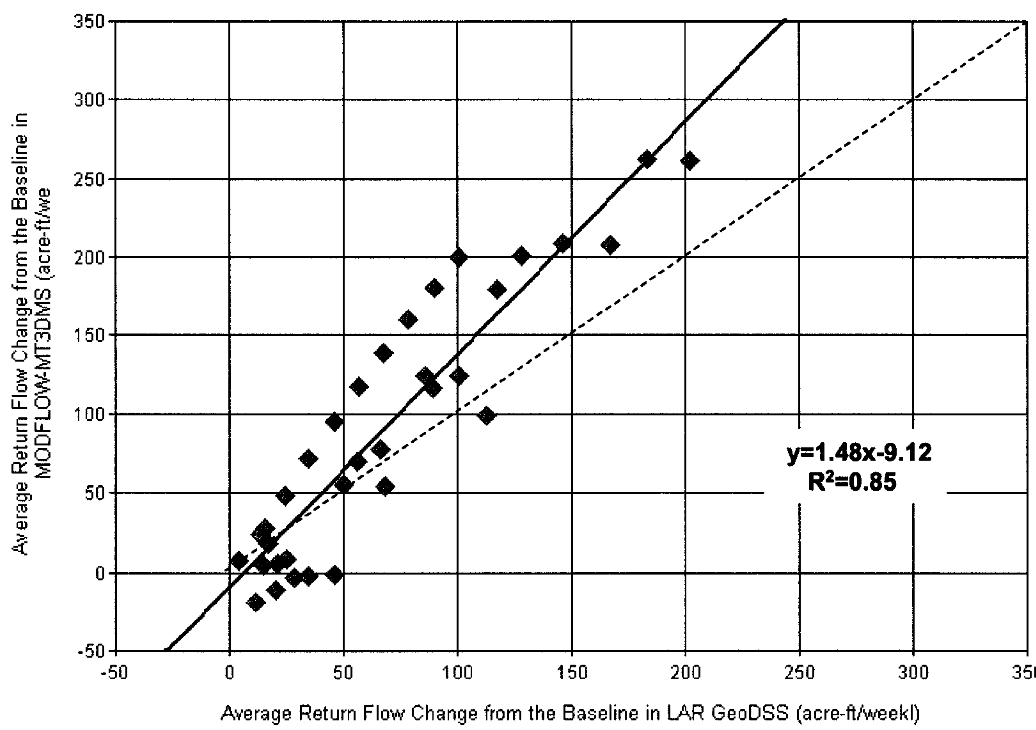


Figure 7.19 – Comparison of the change from the baseline of return flow to the tributaries for the considered management alternatives

Salt load change from the baseline is compared between the *LAR GeoDSS* prediction and the MODFLOW-M3TDMS modeled values in Figure 7.20 for the Arkansas and Figure 7.21 for the tributaries. These results are the product of the flow and concentration predictions, therefore exhibiting both prediction errors. Results are presented excluding grouping area 11 which was shown in the flow analysis to contribute large discrepancies due to the modeled features outside the MODFLOW-MT3DMS modeled area.

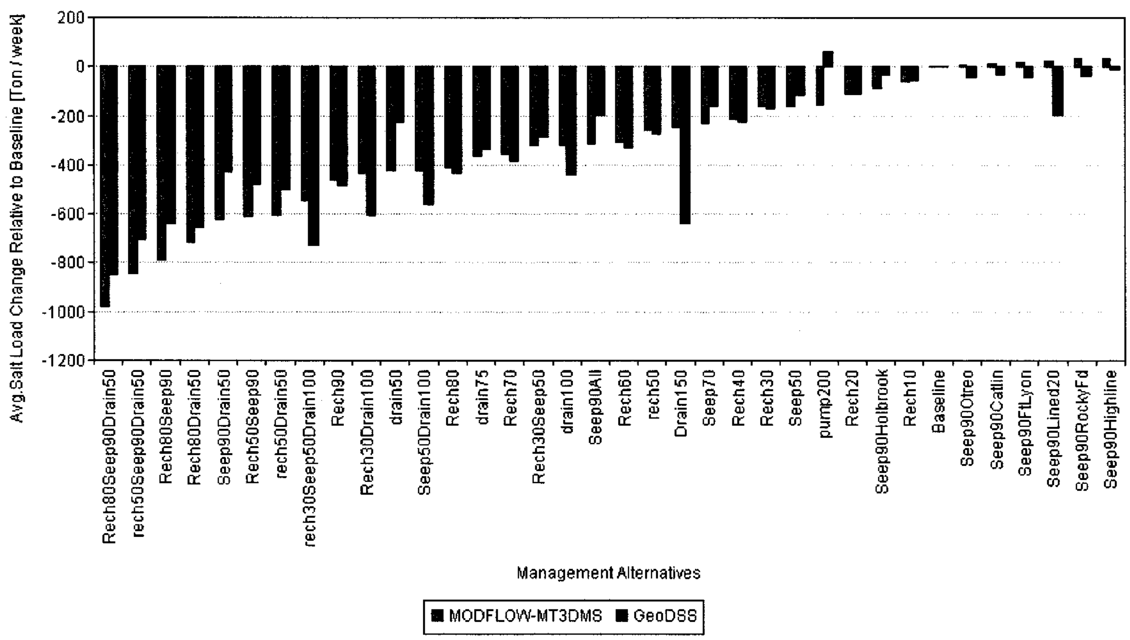


Figure 7.20 – Computed salt load prediction change relative to the baseline for the Arkansas River within the MODFLOW-MT3DMS modeled region for considered management alternatives

The largest discrepancies in Figure 7.20, where change in the *LAR GeoDSS* prediction is larger than change in the MODFLOW-MT3DMS prediction, imply under-prediction of salt loads to the Arkansas River. These discrepancies are mainly caused by a consistent under-prediction of return flows in grouping area 10 combined with a larger reduction of salt concentration than that modeled by MODFLOW-MT3DMS. The system stress changes modeled in the water management alternatives are harder to be fully captured by explanatory variables within small areas, especially when few irrigated fields and canal diversions intersect the grouping area (e.g., grouping area 10); therefore, changes relative to the baseline in these areas are expected to have less capability to adequately represent the MODFLOW-MT3DMS modeled changes.

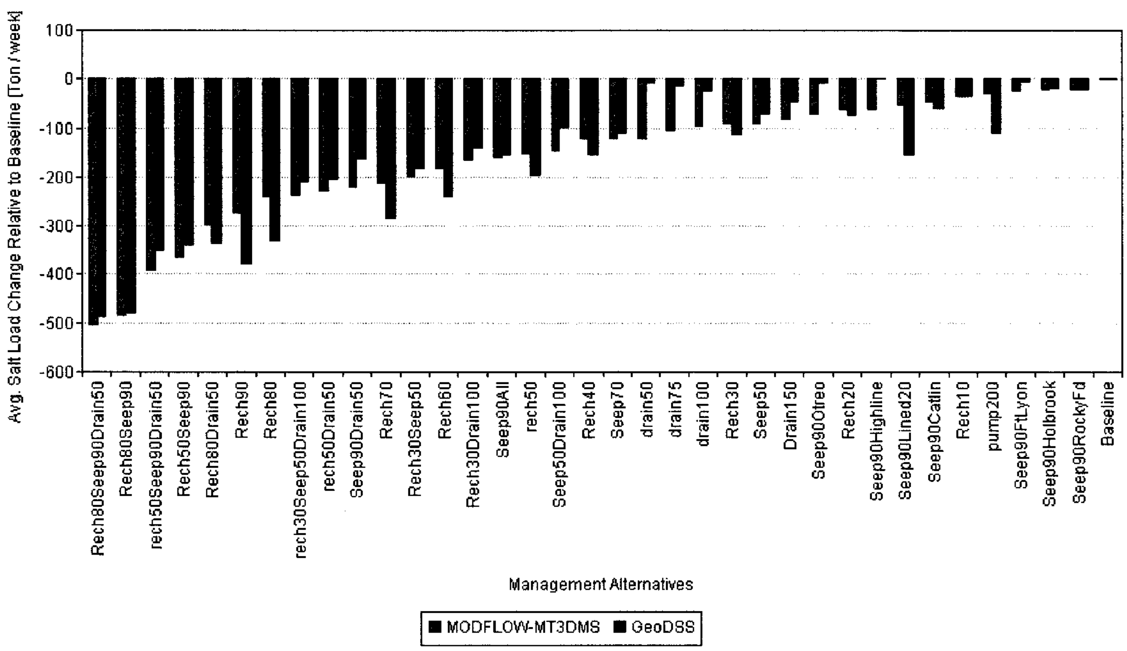


Figure 7.21 – Computed salt load prediction change relative to the baseline for the tributaries within the MODFLOW-MT3DMS modeled region for considered management alternatives

A large portion of the discrepancies in Figure 7.21 between the *LAR GeoDSS* computed and MODFLOW-MT3DMS modeled salt load change occur due to results from grouping area 6. Besides this grouping area being partially modeled in MODFLOW-MT3DMS, it includes a MODFLOW-MT3DMS modeled tributary that crosses into groping area 7 where it converges with the Arkansas River. Although the length of this tributary line within the network is 6.5 km, the MODFLOW-MT3DMS modeled length of the tributary inside grouping area 7 is less than 1 km; therefore, the tributary is not modeled in *LAR GeoDSS*. Not modeling this tributary neglects the return flows inside area 6, contributing an underestimation of return flow in this area.

Description of Sources of Uncertainty in the Stream-Aquifer Interaction Modeling

Although direct coupling of MODFLOW-MT3DMS and Geo-MODSIM could provide stream-aquifer interaction modeling in *LAR GeoDSS*, the ANN-based methodology to model stream-aquifer interaction in *LAR GeoDSS* allows the simulation of conjunctive use of surface and ground water quantity and quality basin-wide utilizing results from only a partial coverage of the basin for which detailed data and MODFLOW-MT3DMS model results were available. Discrepancies presented in the previous sections are in large part a result of the uncertainty in the implemented methodology.

The basin-wide simulation of return flows and salt concentrations require introducing procedures that increase the uncertainty in the predictions observed during the ANN training and testing stage. The ANN priming procedure estimates a likely starting condition based on calculated explanatory variables for the initial time steps but it could introduce a false start error that will propagate over the entire simulation period. The modeled process memory in the ANN explanatory variables, represented by the inclusion of previous time step conditions of the system, is another source of uncertainty. Basin-wide predictions require the use of previously predicted values (i.e., return flows and corresponding concentrations) as explanatory variables, resulting in a propagation of errors that is magnified by the false start error. Simulations for this case study start in a historically wet period (i.e., April 1999) increasing the usual instabilities and oscillations associated with transient finite difference model initial time steps. Although the MODFLOW-MT3DMS results for the very first time steps are excluded from the ANN training, the ANN-based simulation still requires predictions over the initial time steps to guide future predictions. Off-track predictions for the initial time steps could be a cause for the entire simulation predictions to stay off-track, as mentioned in the salt loadings analysis where some of the concentration predictions are uniform under prediction of the change from the baseline.

Basin Scale Predictions

The basin-wide ANN-based predictions of average net return flow to the Arkansas River and tributaries are shown in Figure 7.22. Although stress magnitude and change characteristics may be different when analyzed at the basin scale relative to the regional MODFLOW-MT3DMS modeled area, the results show predictions in the range of those obtained for the modeled area (see Figures 7.6 and 7.8). Basin-wide predictions of changes (generally reductions) in net return flow from the baseline are similar to those analyzed in the previous sections for the *LAR GeoDSS* predictions within the MODFLOW-MT3DMS modeled area.

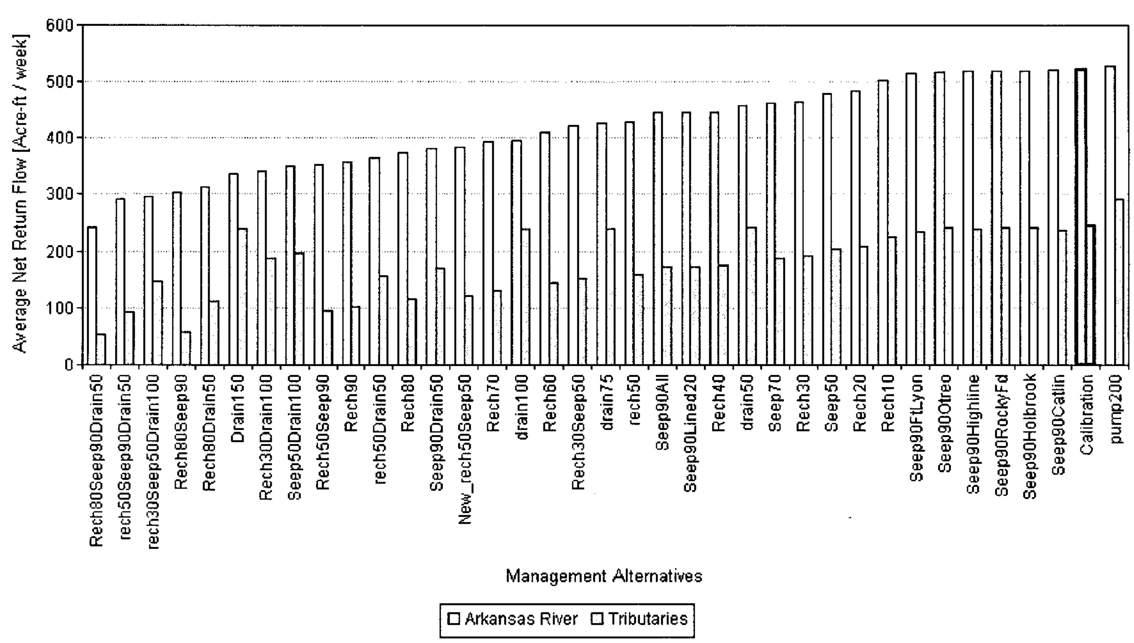


Figure 7.22 – Basin-wide average predicted net return flow per consider water management alternative

The spread of the basin-wide predictions is analyzed computing the CV over all grouping areas and time periods for each water management alternative. Figure 7.23 shows the CV for both the Arkansas River and tributaries net return flow predicted by *LAR GeoDSS*. Over all the simulated water management alternatives, the relative spread of tributary net return flow predictions at the basin scale tend to be larger than the corresponding CVs computed within the MODFLOW-MT3DMS modeled area; contrarily, the Arkansas River net return flow prediction spread are in general reduced in the basin-wide prediction compared to the regional predicted CVs. Changes in the tributary prediction CVs at the basin scale are attributed to the dissimilarity of tributary features modeled in the grouping areas across the basin since length and density of modeled tributaries can change markedly from one grouping area to another. On the other hand, Arkansas River net return flow is predicted for similar lengths of stream in all grouping areas favoring predictions that maintain the relative spread, as observed. Further conglomeration of predictions around the mean can be attributed to less variability of the computed explanatory variables compared with the corresponding values within the MODFLOW-MT3DMS modeled area.

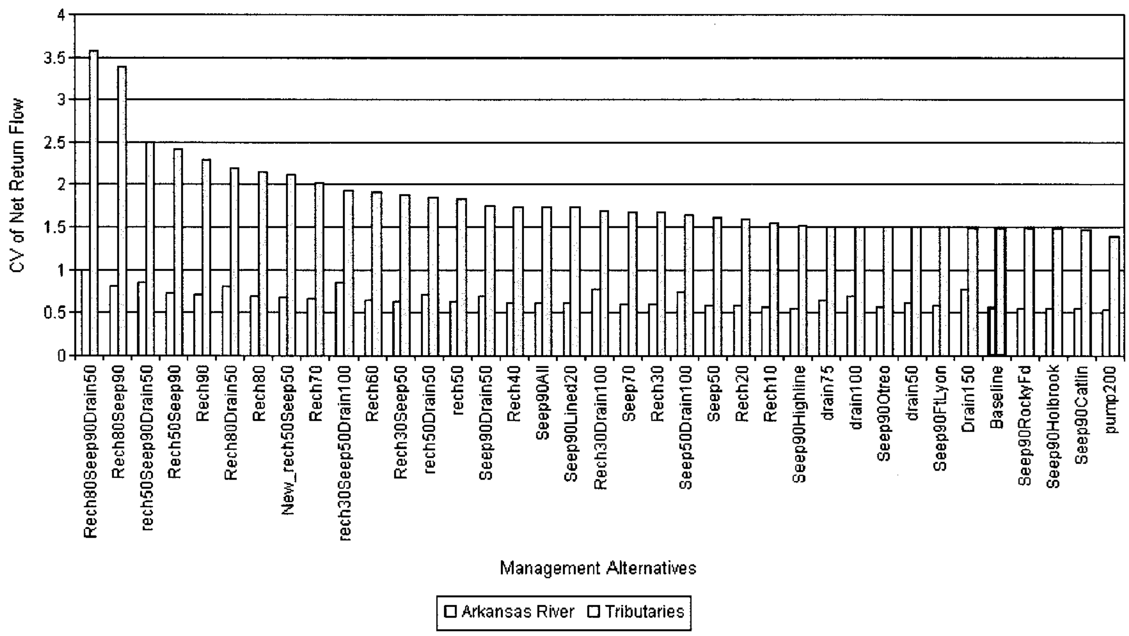


Figure 7.23 – Coefficient of variation of the basin-wide *LAR GeoDSS* predicted net return flow for considered management alternatives

Basin-wide predicted salt loadings and their relative change among the simulated water management alternatives are shown in Figure 7.24. Based on the observed average MODFLOW-MT3DMS modeled values of salt loadings, the *LAR GeoDSS* predicts basin-wide salt loadings that are reasonable, likely having the same under-prediction tendency identified in the previous analysis for predictions inside the MODFLOW-MT3DMS modeled area. No appreciable differences are found between the CVs of the *LAR GeoDSS* predicted salt loadings computed basin-wide and those within the MODFLOW-MT3DMS modeled area, as presented in Figures 7.12 and 7.14.

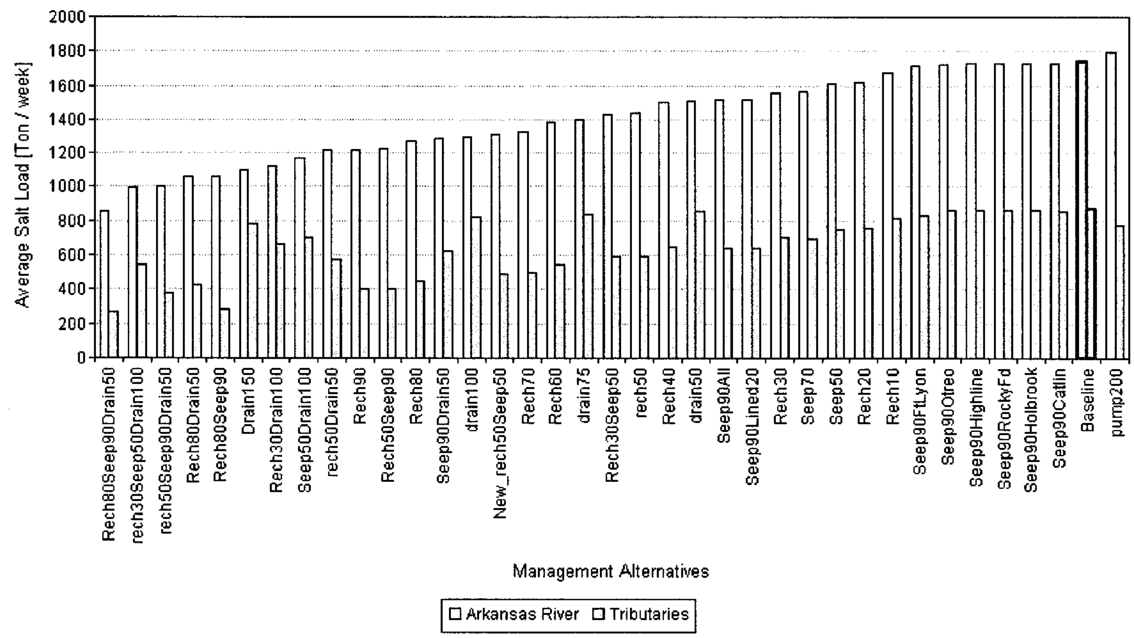


Figure 7.24 – Basin-wide salt loading to the Arkansas River and tributaries predicted by the *LAR GeoDSS* for considered management alternatives

River Water Quality for Operational Mode A

The predicted river basin soil and water quality is improved through the implementation of the management alternatives. Dilution takes place while running the non-diverted river water through the system, replacing more-concentrated return flows with less-concentrated non-diverted water. For the water management alternatives simulated, improvements in water quality throughout the system were evaluated using the average simulated TDS concentrations at key points in the river. The average simulated concentration at the system diversion points indicate improvement in the water applied to the fields with a consequential increase in crop yield and better water quality for municipal and industrial use, reducing water treatment costs. Figure 7.25 presents a summary of the average concentrations of the basin-wide diverted water for the simulated alternatives. Results show an overall reduction in concentration at the diversion points relative to the historical concentrations. This concentration reduction is caused by a dilution effect of water that is not diverted during the management alternatives simulation, replacing more concentrated return flows. Management alternatives with insignificant change in the diverted water concentration correspond to the alternatives with localized area of influence, such as the single canal seepage improvement alternatives. The results show that the best average diverted water concentrations are achieved with the combined alternatives, the best being *Rech80Seep90Drain50.*

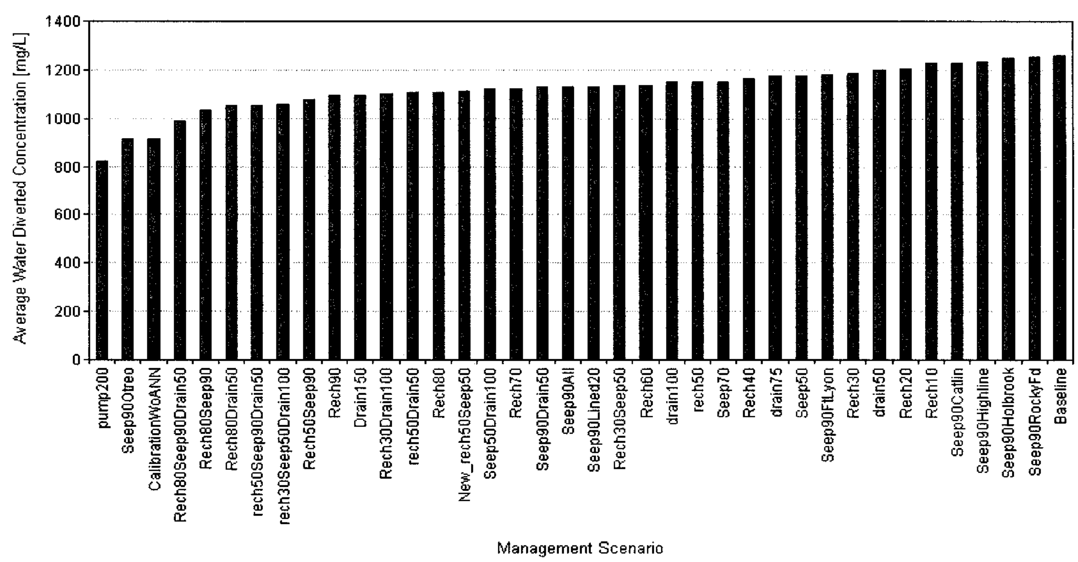


Figure 7.25 – Average diverted water concentration per management alternative in operational mode A

Management alternatives that lower the average concentration of the diverted water improve the quality of the soil by reducing the salt loading to the soil during irrigation, and also imply lower treatment costs for municipal use, resulting in a net basin-wide benefit. The reduction in concentration of diverted water also demonstrates the basin-wide benefit of replacing saline return flows with less concentrated non-diverted water. In addition, the previous results imply that, in most of the alternatives, water transported in the surface system has a lower concentration than that under baseline conditions. Therefore, it could be inferred that water depleted from the stream and canals will have a lower concentration than the modeled water in the baseline, thereby contributing to further improvement in the aquifer water quality.

The predicted salt concentration of flows delivered to Kansas demonstrates that the management alternatives not only provide the volume of water that meets the Arkansas River Compact, but also cause improvement in the water quality. Figure 7.26 summarizes the average concentration of the simulated flows provided to Kansas, with larger reductions corresponding to alternatives with basin-wide influence and more intensive intervention and smaller or insignificant reductions corresponding to alternative with small area of influence or moderate to low levels of improvement. Implementation of the management alternatives produces changes in total salt load at the Colorado-Kansas state line. Figure 7.27 shows the average salt load per week in flows at the Colorado-Kansas state line. Most of the alternatives result in reductions in salt loadings; however, alternatives with the largest increase in water volume to Kansas relative to the baseline result in an increase of salt loadings.

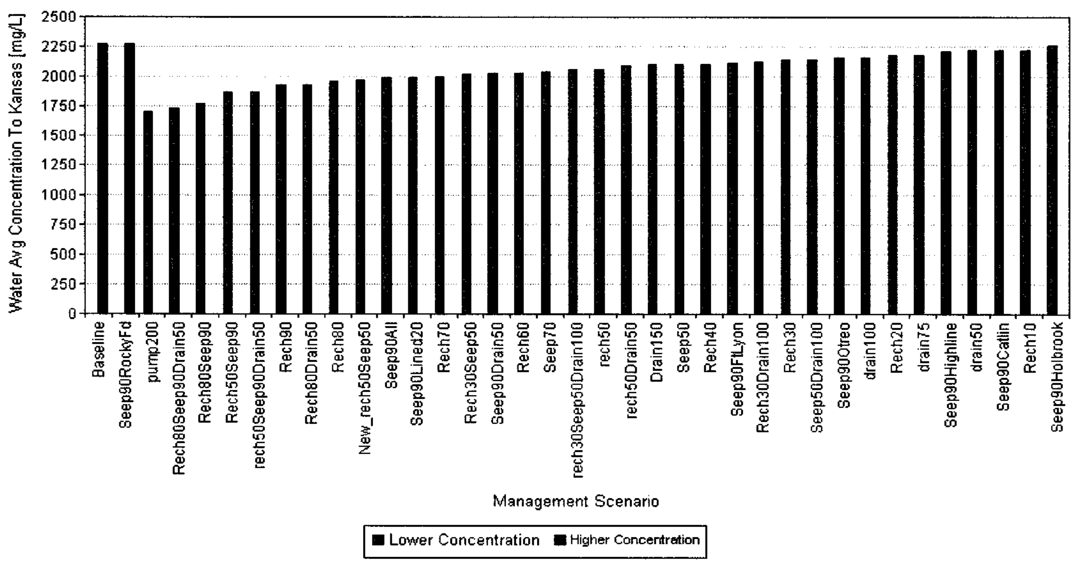


Figure 7.26 – Average water concentration provided to Kansas for considered management alternatives

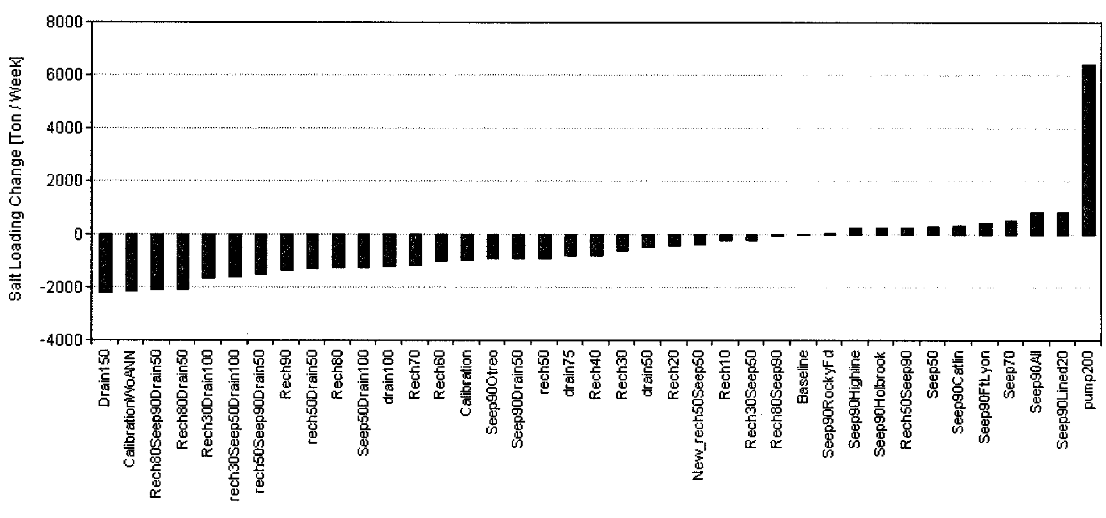


Figure 7.27 – Salt loading change at the Colorado-Kansas state border for considered management alternatives

John Martin Reservoir Salt Transport for Operational Mode A

Water quality entering John Martin Reservoir was analyzed to observe potential improvements in water released from the reservoir. Figure 7.28 shows a summary of the total salt entering from the Arkansas and Purgatoire Rivers and leaving the reservoir during the simulated period per management alternative. Salt load entering the reservoir is used to sort the alternatives display. Results show a reduction of salt load entering and leaving in almost all of the alternative simulations compared to the baseline, indicating an overall lower salt transport through out the system.

The averages of the water quality transport coefficient (Equation 7.24) for the management alternatives are presented in Figure 7.29. The coefficient T_r is greater than one (averaging $\overline{T}_r = 1.37$) for all alternatives, corroborating the assertion that in all cases the salt load released from the reservoir is greater than the load entering the reservoir. The ANN-based simulation in many alternatives resulted in an increase in the transport coefficient, thereby indicating a net larger salt load released per unit load entering the reservoir. The increase in salt loads released from the reservoir is most likely associated with the larger flows being released in this operational mode. As a cursory check, assuming that at least the baseline reservoir release flows are duplicated in the releases occurring under each alternatives, the lower salt loads leaving the reservoir most likely imply a lower concentration downstream.

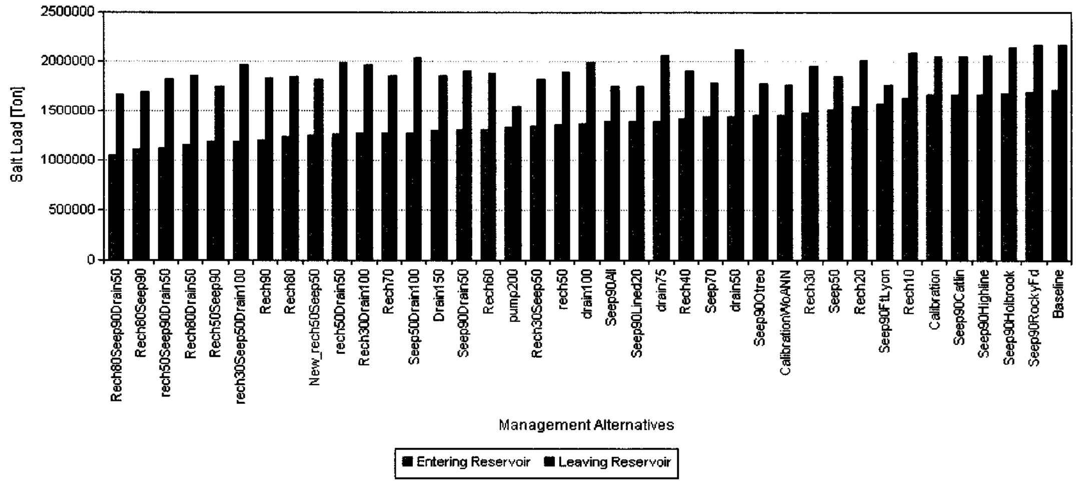


Figure 7.28 – Salt balance in John Martin Reservoir for operational mode A for considered management alternatives

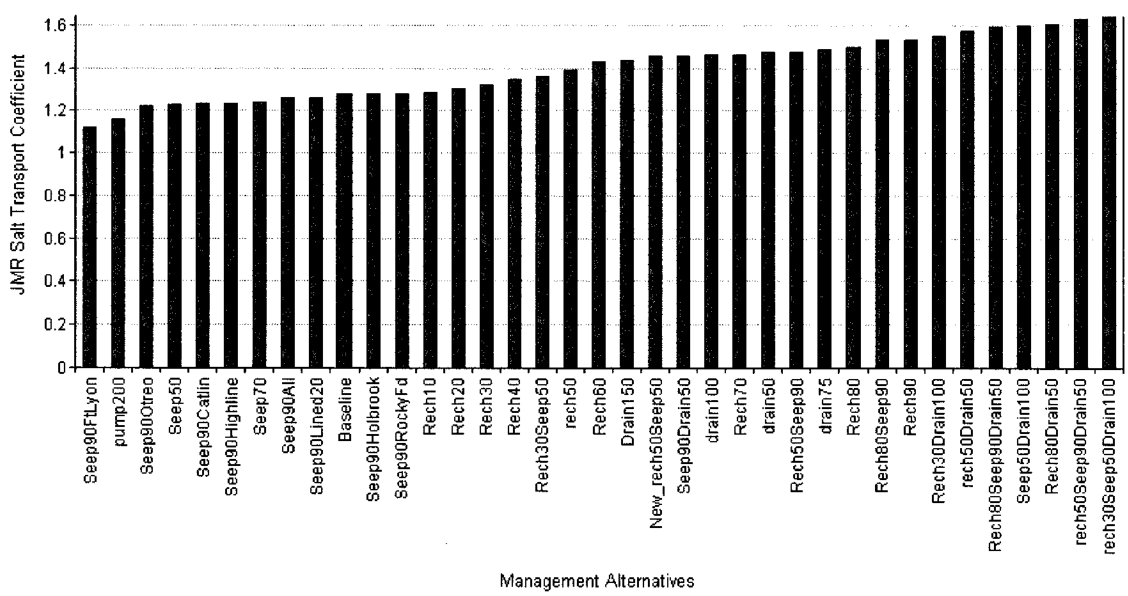


Figure 7.29 – John Martin Reservoir water quality transport coefficient in operational mode A for considered management alternatives

<u>Remarks on Results under Operational Mode A</u>

Although, in this mode the reservoirs did not store additional water and release it to match baseline return flows, the mode assumes that (1) all users in the basin participate in the program (i.e., less water is diverted) and (2) the non-diverted water runs downstream along the river within the same time step. Therefore, the occurrence of relatively small or no shortages indicates that the dynamics of the system would allow implementation of several management alternatives with minimum changes to the operating polices. In the case that the water allowed non-diverted flows could be earmarked for agricultural activities, this water could be added to the natural flow and increase available flows to downstream users in the basin. In this situation, junior diversions that historically diverted less water than their actual water demand could divert more to meet water demands, without implying non-participation in the program and without bringing more agricultural land into production. It is important to point out that the simulated period was historically a transition from wet to dry conditions. The stream-aquifer system modeled is probably in transition to a new dynamic equilibrium that is going to affect the storage water requirements, requiring more water from storage if return flows are reduced once the new dynamic equilibrium is reached. Extending the simulation period will reveal the storage requirement for this dynamic equilibrium condition.

The analysis of the stream-aquifer interaction modeling in the *LAR GeoDSS* reveals reasonable agreement in the percentage of the volume change from the baseline net return flows. Comparisons between the regional MODFLOW-MT3DMS-modeled results and the basin-wide *LAR GeoDSS* results show a reasonably similar tendency (i.e., direction of change) in the overall predictions. Average salt concentrations of aquifer return flows in MODFLOW-MT3DMS for the simulated alternatives showed small disagreement with respect to the baseline concentrations. Changes in average return flow concentrations modeled by MODFLOW-MT3DMS relative to the baseline for all the management alternatives ranges from -32 mg/L and +96 mg/L, which in most of the cases is expected to be smaller than the average ANN predicted concentration error due to the ANN imperfect explanatory variables and the ANN priming procedure. Therefore, it is believed that return flow concentrations for alternatives simulated in the *LAR GeoDSS* with average predicted concentrations that fail to agree with the direction of the change modeled in MODFLOW-MT3DMS have little impact on interpretation of the results.

Table 7.3 shows a summary of the performance of the considered management alternatives for the primary evaluation criteria. Total water shortages greater than 100 acre-ft (123,348.2 m^3) during the simulated period are considered infeasible and labeled as *large*, while small shortages are defined as those greater than zero and less than or equal to 100 acre-ft. The system end-of-storage is compared with the historical volume, considering *lower* conditions to be those where water is left in the reservoirs but is lower than the historical volume. The reservoir system condition *empty* occurs when there is no water left after the simulation and is considered as infeasible. Simulations that are unable to match historical flows at the Colorado-Kansas state line are in *violation* with the Arkansas River Compact, therefore they are considered as infeasible. The stream-aquifer interaction predictions are presented in three groups based on the Arkansas River and tributaries sum of RMSE in change from the baseline. The alternatives with a RMSE sum smaller than 150 acre-ft/week are placed in the *smaller* error group, and alternatives with RMSE sum larger than 250 acre-ft/week are the *larger* group, all other alternatives are in the *average* group. Similar methodology is used to classify water quality predictions for the alternatives, using the RMSE sum of the difference of salt load change from the baseline. The category *smaller* is assigned to the sum of RMSEs smaller than 300 ton/week, the *larger* category is assigned to alternatives with sum of RMSE larger than 600 ton/week and the *average* category is used for alternatives sum of RMSEs between the *smaller* and *larger* groups. The average salt concentration of the flow to Kansas is compared with the historical. Average concentration changes within 5% of the historical concentration are considered as *same*, concentration reductions of up to or equal to 10% of the historical are grouped into *good*, concentration reductions between 10% and 20% are grouped into *better*, and improvements in TDS concentration of more than 20% are categorized as *best.*

This table can guide decision making for implementation of the management alternatives and help focus efforts on future modeling refinements such as improvements in drained water modeling, return flow modeling for type of scenarios with larger errors, and longer term modeling for lower than historical end of storage alternatives.

Table 7.3 – Summary Management Alternative Performance for System Operational Mode A

Alternative Name	Water Shortages	End-of-Simulation Storage Relative to Historical	Relative Aquifer-Stream Interaction Modeling Error		Flow to Kansas (Ark. River Compact)	
			Quantity	Quality	Quantity	Quality
Drain100	Large	Empty	Average	Larger	Violation	Good
Drain150	Large	Empty	Average	Larger	Agreement	Good
Drain50	Large	Empty	Larger	Larger	Violation	Same
Drain75	Large	Empty	Average	Larger	Agreement	Good
New_rech50Seep50	Small	Lower	N/A	N/A	Agreement	Better
Pump200	None	Equal	Average	Average	Agreement	Best
Rech10	Small	Lower	Smaller	Smaller	Agreement	Same
Rech20	Small	Lower	Smaller	Smaller	Agreement	Good
Rech30	Small	Lower	Smaller	Smaller	Agreement	Good
Rech30Drain100	Large	Empty	Average	Larger	Violation	Good
Rech30Seep50	Small	Lower	Average	Average	Agreement	
Rech30Seep50Drain100	Large	Empty	Larger	Larger	Violation	Good
Rech40	Small	Lower	Smaller	Smaller	Agreement	
Rech50	Small	Lower	Smaller	Smaller	Agreement	Good
Rech50Drain50	Large	Empty	Larger	Larger	Agreement	Good
Rech50Seep90	Small	Lower	Larger	Larger	Agreement	Best
Rech50Seep90Drain50	Small	Lower	Larger	Larger	Agreement	Best
Rech60	Small	Lower	Average	Average	Agreement	Better
Rech70	Small	Lower	Average	Average	Agreement	Better
Rech80	Small	Lower	Average	Average	Agreement	Better
Rech80Drain50	Large	Empty	Larger	Larger	Agreement	Better
Rech80Seep90	Small	Lower	Larger	Larger	Agreement	Best
Rech80Seep90Drain50	Small	Lower	Larger	Larger	Agreement	Best
Rech90	Small	Lower	Larger	Average	Agreement	Better
Seep50	Small	Equal	Smaller	Smaller	Agreement	Better
Seep50Drain100	Large	Empty	Average	Larger	Violation	Good
Seep70	Small	Equal	Smaller	Average	Agreement	Better
Seep90All	Small	Equal	Average	Average	Agreement	Better
Seep90Catlin	None	Equal	Smaller	Smaller	Agreement	Same
Seep90Drain50	Small	Lower	Larger		Agreement	Better
Seep90FtLyon	None	Equal	Smaller	Smaller	Agreement	Good
Seep90Highline	None	Equal	Smaller	Smaller	Agreement	Same
Seep90Holbrook	Small	Equal	Smaller	Smaller	Agreement	Same
Seep90Lined20	Small	Equal	Average	Average	Agreement	Better
Seep90Otero	Small	Lower	Smaller	Average	Agreement	Good
Seep90RockyFd	Small	Equal	Smaller	Smaller	Agreement	Better

Reservoir Operational Mode B

In this reservoir operational mode, the baseline flows and concentrations failed to match the calibration values, contrary to the situation observed in the Mode A. The baseline calibration network, called *calibration*, in Mode B used historical storage target levels and the *baseline* case stored water using the reservoir layer balancing algorithm. The management alternatives are compared against the baseline since they will use the same storage allocation algorithm. The computed water demands for this operational mode result in the same amounts as for Mode A (see Figure 7.2).

Water Allocation and Shortages for Operational Mode B

Water shortages are summarized for this operational mode to identify alternatives that are unable to meet the water rights and river compact requirements. Figure 7.30 shows the water demand shortage per alternative. Guaranteeing the adequate water rights allocation requires that there can be no water shortages. Alternatives with significant shortages are flagged as infeasible unless additional action is taken to supply the required water. Table 7.4 lists alternatives with significant shortages in contrast to the Mode A results. All alternatives not listed in Table 7.4 exhibit zero water shortages. Comparing Table 7.4 and Table 7.2, it is evident that improvements are insufficient to render any of the alternatives in Table 7.2 as being feasible. In most cases, there is a slight increase in total shortages due to changes in return flow patterns caused by alterations in the system operation rules.

Table 7.4 – Management Alternatives with Water Shortages in Operational Mode B

Alternative Name	Water Shortage [Acre-ft]
Rech80Drain50	10557
Drain50	20901
Rech50Drain50	28811
Rech30Seep50Drain100	85461
Seep50Drain100	92853
Drain75	95170
Rech30Drain100	156393
Drain100	160524
Drain150	273136

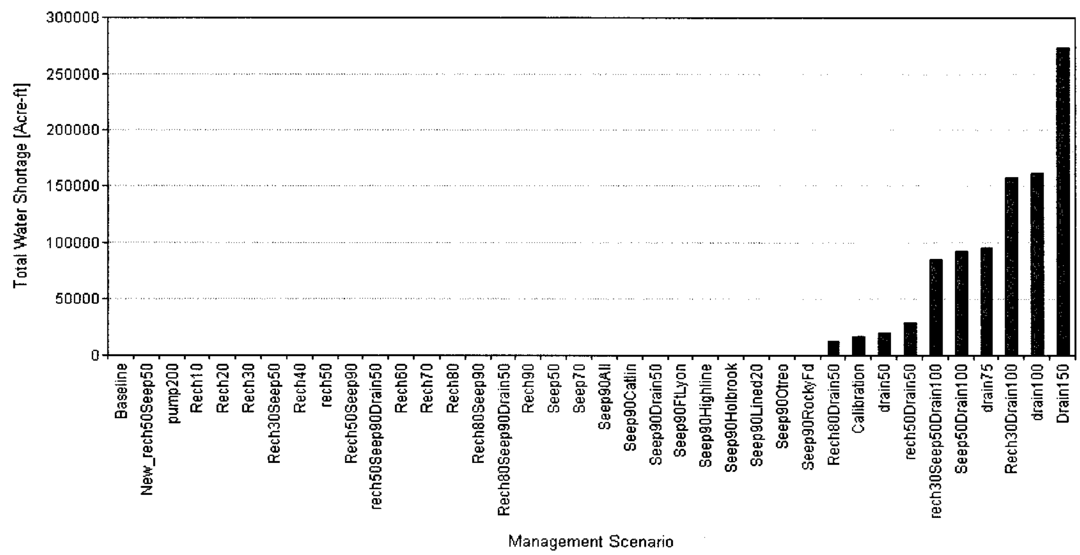


Figure 7.30 – Management alternatives water demand shortage for operational mode B for considered management alternatives

Reservoir Storage and Operation for Operational Mode B

In this mode the reservoir layers and costs were set so as to duplicate the historical operation. The reservoir priorities were set in such a way that all of the water demands and river compact requirements are satisfied. Since this mode allows storage above the historical storage, results should show the most efficient allocation of water by storing non-diverted water and releasing strictly the water required to satisfy water rights and the river compact. The end-of-simulation system storage for each alternative is plotted in Figure 7.31, including the baseline for comparison. As found for Mode A, alternatives with shortages show no water stored in the reservoirs at the end of the simulation, indicating the lack of enough resources in the system to make up for the changes in return flows. Table 7.5 shows the end-of-simulation storage for the alternatives, with the *additional storage* column corresponding to the difference in end-of-simulation storage between the baseline and the given alternative.

Table 7.5 – Alternatives End-of-Simulation Reservoir Storage (operational Mode B)

Alternative Name	**Additional Storage [Acre-ft]**	**End-of-simulation Storage [Acre-ft]**	**Alternative Name**	**Additional Storage [Acre-ft]**	**End-of-simulation Storage [Acre-ft]**
Drain100	-145192	0	Rech50Seep90Drain50	-5788	139404
Drain150	-145192	0	Rech80	-2656	142536
Drain50	-145192	0	**Baseline**	**0**	**145192**
Drain75	-145192	0	**Calibration**	**0**	**145192**
Rech30Drain100	-145192	0	Seep90Holbrook	4337	149529
Rech30Seep50Drain100	-145192	0	Rech90	8839	154031
Rech50Drain50	-145192	0	Seep90Catlin	25912	171104
Rech80Drain50	-145192	0	Seep90Highline	27123	172315
Seep50Drain100	-145192	0	Rech80Seep90Drain50	45088	190280
Rech40	-24927	120265	Rech30Seep50	53520	198712
Rech30	-24566	120626	New_rech50Seep50	58575	203767
Rech50	-22005	123187	Seep50	62388	207580
Seep90Drain50	-21107	124085	Seep90FtLyon	79419	224611
Seep90Otreo	-19487	125705	Seep70	97235	242427
Rech20	-19099	126093	Seep90All	138927	284119
Rech60	-17434	127758	Seep90Lined20	138927	284119
Rech10	-12921	132271	Rech50Seep90	150337	295529
Rech70	-11286	133906	Rech80Seep90	197779	342971
Seep90RockyFd	-9870	135322	Pump200	364534	509726

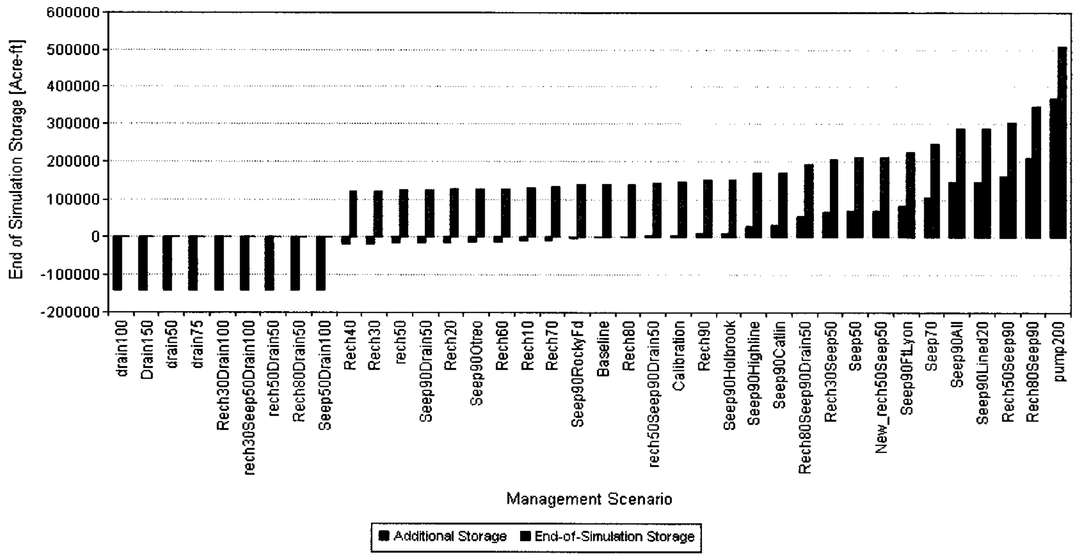


Figure 7.31 – Management alternatives end-of-simulation system storage in operational mode B

Stored water at the end of the simulation indicates that the alternative implementation produces water that can be used to further improve water quality in the system or in environmental programs and if water law allows it, provides possibilities of additional appropriation. This water could be released on-demand to reach water quality goals at selected points in the system. The possibility of storing and releasing this additional water in the actual system requires further investigation and negotiation with river administrators and system operators.

Arkansas River Compact Compliance for Operational Mode B

The Kansas flow check summary is presented in Figure 7.32. Operational mode B provides, if available, exactly the river compact requested water. This mode is able to store any additional water by releasing only what is necessary. The *Pump200* alternative is the only one that provides Kansas with additional water. This alternative includes vertical drainage water downstream of John Martin Reservoir that cannot be retained in the reservoir by exchanges for the releases. Except for alternative *Seep50Drain100*, the alternatives with zero storage at the end of the simulation (Table 7.5) violate the river compact at some point in the simulation.

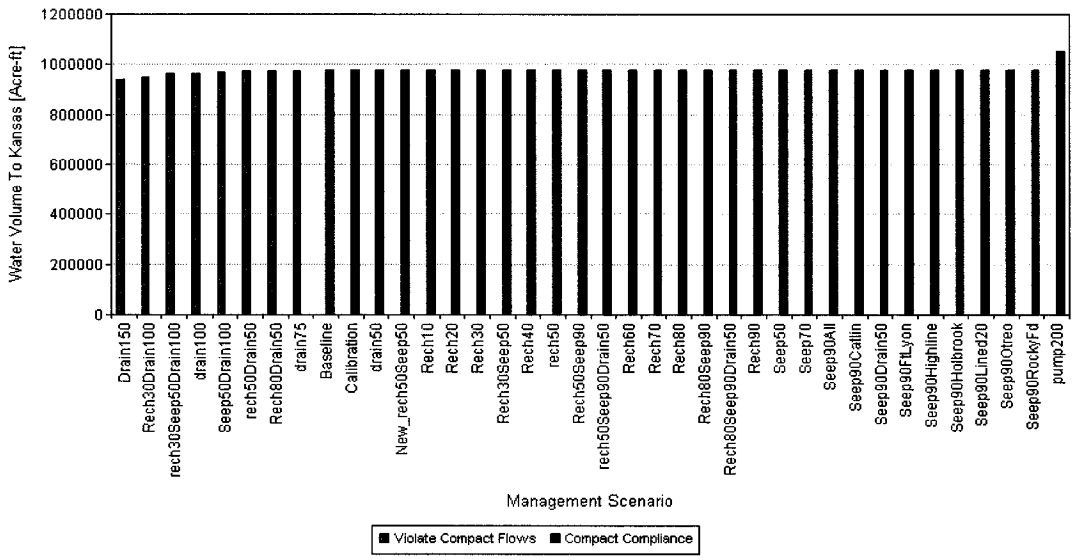


Figure 7.32 – Alternatives Colorado-Kansas state line flow in operational Mode B for considered management alternatives for considered management alternatives

<u>Aquifer-Stream Interaction for Operational Mode B</u>

Although, in this operational mode the modeled stream-aquifer interaction is expected to slightly change from that in Mode A due to changes in flows in the Arkansas River and in diverted water, as shown in Chapter 6, there is only a small difference in the return flow prediction between Mode A and Mode B. For practical purposes, the stream-aquifer interaction results are assumed to not change significantly in comparison to Mode A (see Figures 7.12, 7.13 and 7.14).

River Water Quality for Operational Mode B

The simulated water management alternative improvements in the system water quality at the diversion points are summarized in Figure 7.33. Comparison of the change in average diversion TDS concentrations between Mode A and B for each alternative indicate that Mode B has a tendency to provide diversion water with slightly higher concentrations than Mode A. The more concentrated diversions are caused by storing any additional water upstream in the reservoirs in Mode B, instead of releasing it to flow downstream as in Mode A. The average change in diversion concentration is 36.7 mg/L (less than 4% change from the average concentration computed in Mode A), the maximum is 109.4 mg/L and the minimum is -35.5 mg/L over all alternatives. The water management alternatives showing a decrease in the diverted concentration are: *Rech80Seep90*, *rech50Seep90Drain50*, *Drain150*, *Seep50Drain100*, *drain100*, *drain75*, *Rech30Drain100* and *Rech80Seep90Drain50.*

Figure 7.34 illustrates the simulated average TDS concentration of the water provided to Kansas. In general, results show a marginal increase in concentration as compared with the Mode A simulated concentrations. For all management alternatives with lower average TDS concentration than the baseline in Mode A, *Seep90Holbrook* is the only alternative that shows a higher concentration in Mode B. The change in average concentration between the operational modes per alternative is shown in Figure 7.35. The average change in concentration of 41.4 mg/L reiterates the overall higher concentration in the Mode B simulations as a consequence of the lower flows through out the system.

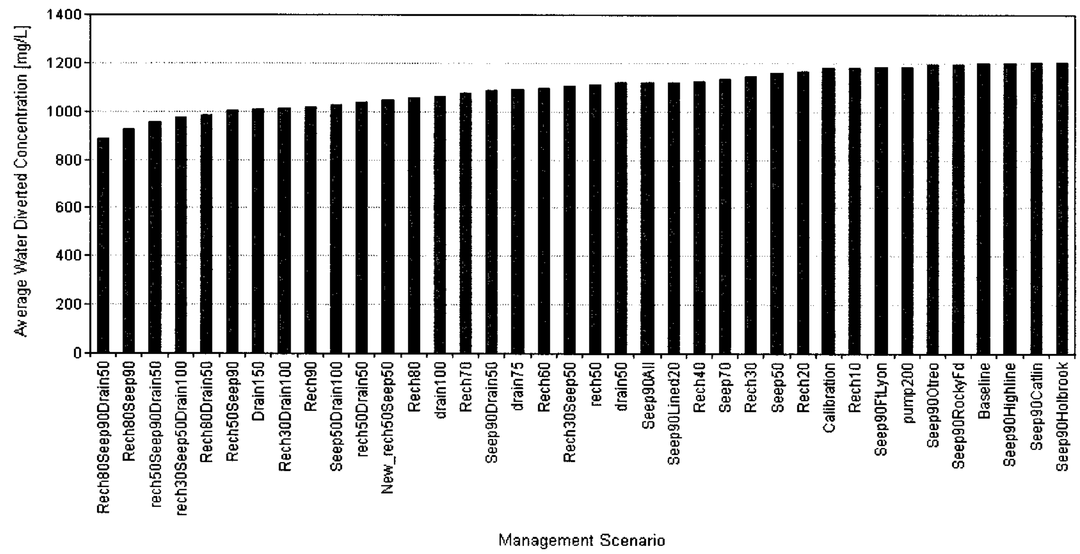


Figure 7.33 – Average TDS concentration in diverted flow per water management alternative in operational Mode B

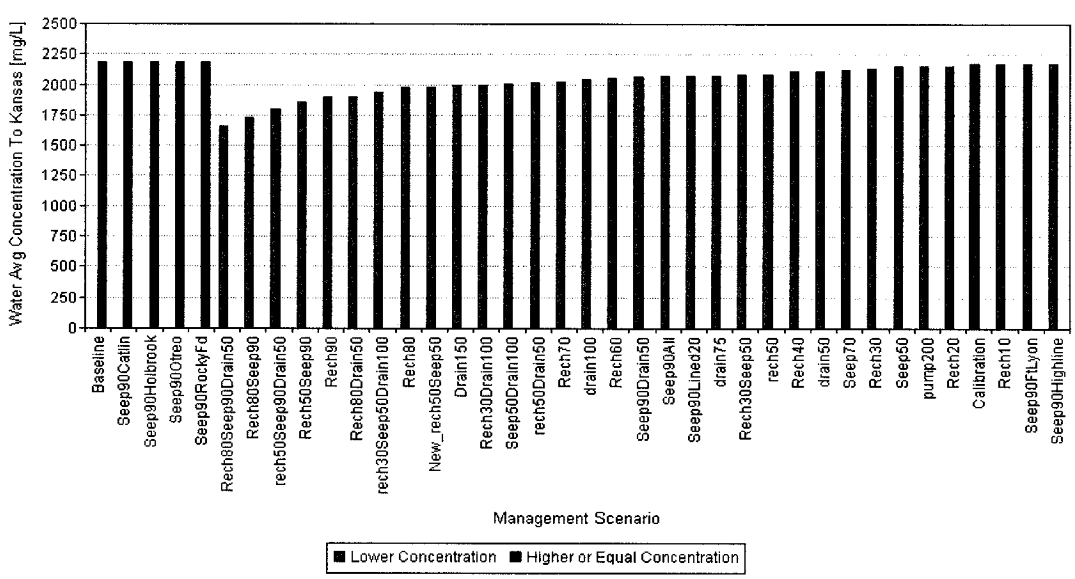


Figure 7.34 – Average TDS concentration provided to Kansas in operational Mode B for considered management alternatives

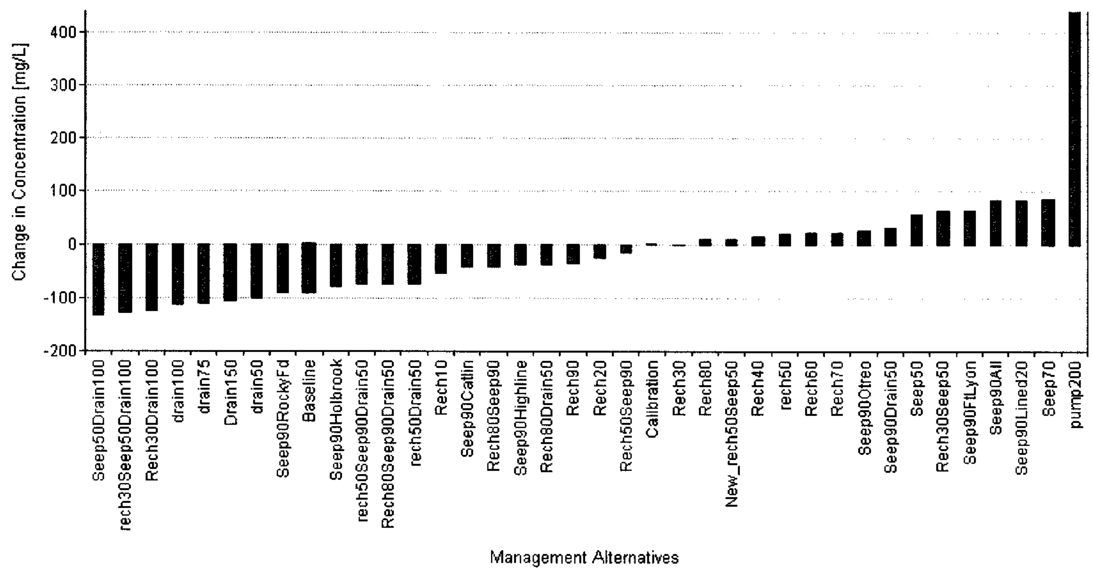


Figure 7.35 – Change in TDS concentration in flows to Kansas between Mode A and Mode B for considered management alternatives

<u>John Martin Reservoir Salt Transport for Operational Mode B</u>

Total predicted salt loads entering and leaving John Martin Reservoir under Mode B are presented in Figure 7.36. With the exception of *Rech80Seep90Drain50* and *Rech80Seep90*, results show a decrease in salt load from the Arkansas and Purgatoire Rivers to John Martin Reservoir. The average load reduction in the Mode B alternative is 85,080 tons. The salt released from the reservoir tends to increase by 105,483 tons on average. The average water quality transport coefficient for each management alternatives is presented in Figure 7.37. The average salt transport coefficient ($\overline{T}_r = 1.53$) for Mode B increases slightly from the average for Mode A, most likely due to the reservoir operation reduced releases compared with Mode A. The only alternative with a transport coefficient value less than one is *Pump200*.

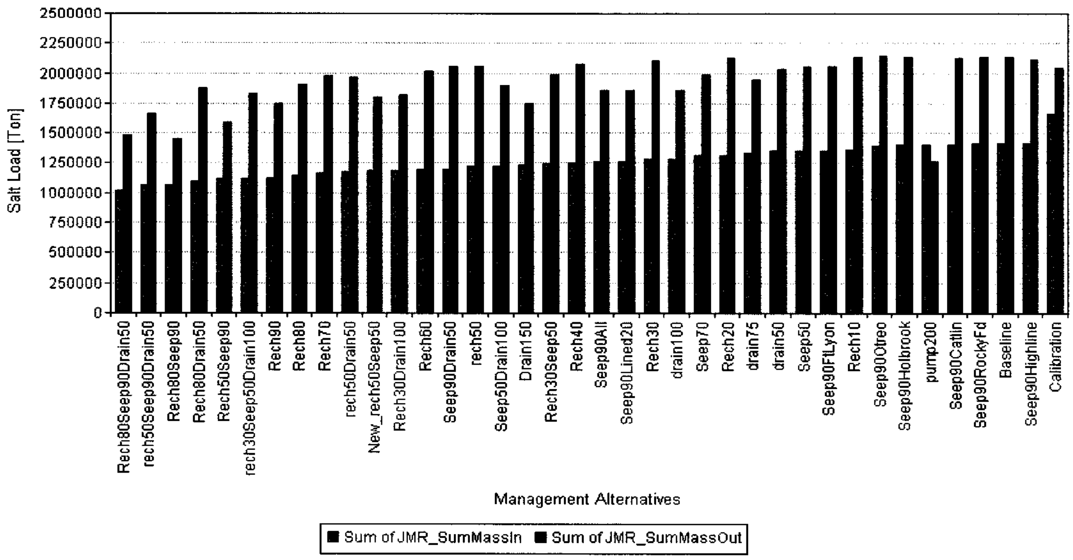


Figure 7.36 – Salt balance in John Martin Reservoir for operational Mode B for considered management alternatives

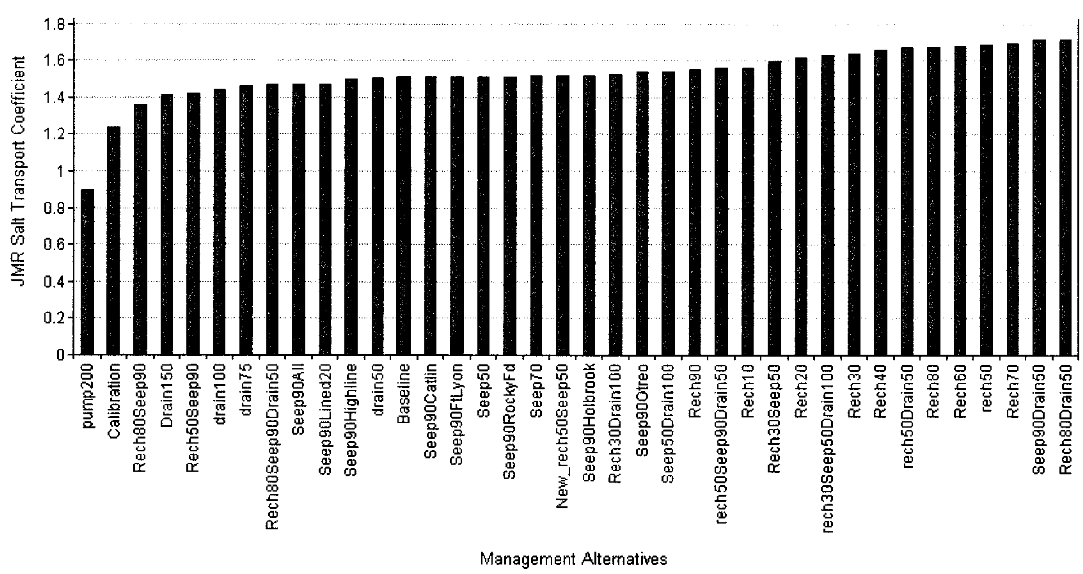


Figure 7.37 – John Martin Reservoir water quality transport coefficient for management alternatives under operational Mode B for considered management alternatives

Detailed results on system performance for all management alternatives under operational Mode B can be found in Appendix VI – *Reservoir Operational Mode B.*

Remarks on Results under Operational Mode B

The comparison of simulation results between modes A and B show marginal positive effects in the river water quality, and in some cases detrimental impacts in using Mode B reservoir operation. However, these results are expected since less water is moving downstream because it is being stored in the reservoirs. The real benefit of Mode B is in having additional end-of-simulation storage, since a potential environmental improvement could be achieved by releasing the additional water to meet water quality targets at selected locations within the basin, maximizing the effects of the water management alternatives implementation.

This reservoir modeling approach assures exact releases from the reservoirs to meet all water demands, which could result in no releases required for weeks. This situation creates problems in the water quality calibration since small or zero flows in the main stem amplify the effects of salt contributions from the tributaries, thereby making calibration more difficult. The effect of small or zero flows in the river causes spikes of high concentrations that can affect the ANN-based reservoir salt transport results. This aspect of the reservoir layer balancing approach should be addressed in future refinements of the modeling system.

Table 7.6 shows a summary of the performance of the management alternatives in relation to specified evaluation criteria. The table summarizes *large* water shortage for the simulated period when greater than 100 acre-ft. The reservoir system storage is categorized depending on the end-of-simulation storage with respect to the historical, with *empty* assigned to infeasible simulations having dry conditions in the reservoirs. Management alternatives are categorized in *violation* with the Arkansas River Compact if the simulation results are unable to provide at least the historical flows to Kansas. The average salt concentration is compared with both the historical and the operational Mode A. Average concentration changes within 5% of the historical concentration are considered as *same*, concentration reductions of up to or equal to 10% of the historical are grouped into *good*, concentration reductions between 10% and 20% are grouped into *better*, and improvements in TDS concentration of more than 20% are categorized as *best*. This table helps identify alternatives that would be more intricate to implement and alternatives with more potential for water quality improvement.

Table 7.6 – Summary Management Alternative Performance for System Operational Mode B

Alternative Name	Water Shortages	End-of-Simulation Storage Relative to Historical	Flow to Kansas		
			Ark. River Compact	Concentration relative to historical	Conc. Change From Mode A
Drain100	Large	Empty	Violation	Better	Same
Drain150	Large	Empty	Violation	Better	Same
Drain50	Large	Empty	Agreement	Good	Same
Drain75	Large	Empty	Violation	Good	Same
New_rech50Seep50	None	Above	Agreement	Better	Higher
Pump200	None	Above	Agreement	Good	Higher
Rech10	None	Below	Agreement	Same	Higher
Rech20	None	Below	Agreement	Same	Higher
Rech30	None	Below	Agreement	Good	Higher
Rech30Drain100	Large	Empty	Violation	Better	Same
Rech30Seep50	None	Above	Agreement	Good	Higher
Rech30Seep50Drain100	Large	Empty	Violation	Better	Higher
Rech40	None	Below	Agreement	Good	Higher
Rech50	None	Below	Agreement	Good	Higher
Rech50Drain50	Large	Empty	Violation	Better	Higher
Rech50Seep90	None	Below	Agreement	Best	Higher
Rech50Seep90Drain50	None	Below	Agreement	Best	Lower
Rech60	None	Below	Agreement	Good	Higher
Rech70	None	Below	Agreement	Better	Higher
Rech80	None	Below	Agreement	Better	Higher
Rech80Drain50	Large	Empty	Violation	Better	Higher
Rech80Seep90	None	Above	Agreement	Best	Lower
Rech80Seep90Drain50	None	Above	Agreement	Best	Lower
Rech90	None	Above	Agreement	Best	Higher
Seep50	None	Above	Agreement	Good	Higher
Seep50Drain100	Large	Empty	Agreement	Better	Lower
Seep70	None	Above	Agreement	Good	Higher
Seep90All	None	Above	Agreement	Good	Higher
Seep90Catlin	None	Above	Agreement	Better	Higher
Seep90Drain50	None	Below	Agreement	Good	Higher
Seep90FtLyon	None	Above	Agreement	Same	Higher
Seep90Highline	None	Above	Agreement	Same	Higher
Seep90Holbrook	None	Above	Agreement	Better	Higher
Seep90Lined20	None	Above	Agreement	Good	Higher
Seep90Otero	None	Below	Agreement	Better	Higher
Seep90RockyFd	None	Below	Agreement	Better	Higher

Analysis of Stream-Aquifer Results

The stream-aquifer interaction results need to be interpreted in the context of the MODFLOW-MT3DMS modeling, thereby analyzing the aquifer flow budget components to understand changes in the aquifer behavior under various management alternatives. MODFLOW-MT3DMS output files were processed using Geo-MODFLOW, where the flow budget components were summarized for the entire simulated area, to compare volume differences between a sample management alternative and the baseline simulation. The MODFLOW flow budget is composed of: Aquifer Storage, Wells, Rivers, Recharge, Evaporation (up-flux from the water table), Drainage, and General Heads (Seepage). Net changes in these components from the baseline simulation are examined for the water management scenario *Rech50*, which reduces irrigation-induced areal aquifer recharge by 50 percent. In this comparison, results show the following tendencies: (1) areal recharge reduction, (2) canal seepage increase, (3) reduction in upflux from the water table, (4) net return flow decrease, (5) aquifer storage decrease, and (6) no change in the pumping. Although the management scenario only includes reduction in the areal aquifer recharge, changes in the water table depth affect the system dynamics including computed canal seepage, return flow, and upflux. Figure 7.38 depicts weekly changes in MODFLOW flow budget components between the *Rech50* scenario and the baseline simulation.

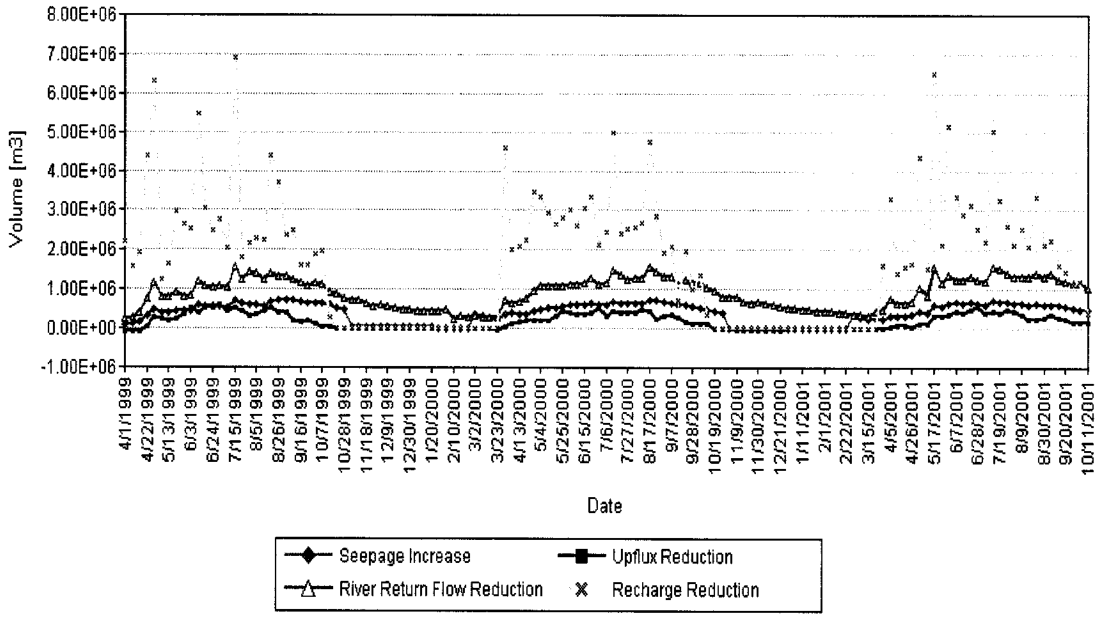


Figure 7.38 – MODFLOW Flow Budget components change for 50% areal recharge reduction alternative compared to the baseline

For understanding the changes to the groundwater system, the terms implying water additions (gains) to the baseline aquifer conditions are combined together. Components resulting in more water available to the aquifer include river return flow reductions, canal seepage increases, and the reduction in upflux from the water table. In contrast, areal recharge reduction represents less water to the aquifer (irrigation losses) during the alternative modeling. Figure 7.39 presents the comparison between the additions/subtractions to the baseline aquifer water. The difference between additions and subtractions in Figure 7.39 indicates the change in aquifer storage. The total simulated aquifer gains are $2.00\text{x}10^8$ m^3 (162,142 acre-ft) and the total simulated aquifer losses are $2.28\text{x}10^8$ m^3 (185,004 acre-ft), indicating that approximately 12% of the water lost was derived from aquifer storage depletion. Figure 7.40 shows the change in aquifer storage from the baseline storage, where positive values indicate release of water from storage and negative values represent additional water to storage. The accumulated storage over the simulated period shows that during this alternative simulation, the aquifer storage is depleted. Since the river return flows are the only dynamic component of the flow budget modeled in the basin scale modeling system, the aquifer depletion reflects a net gain of water to the surface system. Since the areal recharge reduction amounts are not diverted at the canal head gates, while the aquifer return flow reductions are less than the reduction in areal recharge, a false impression of water savings can be created.

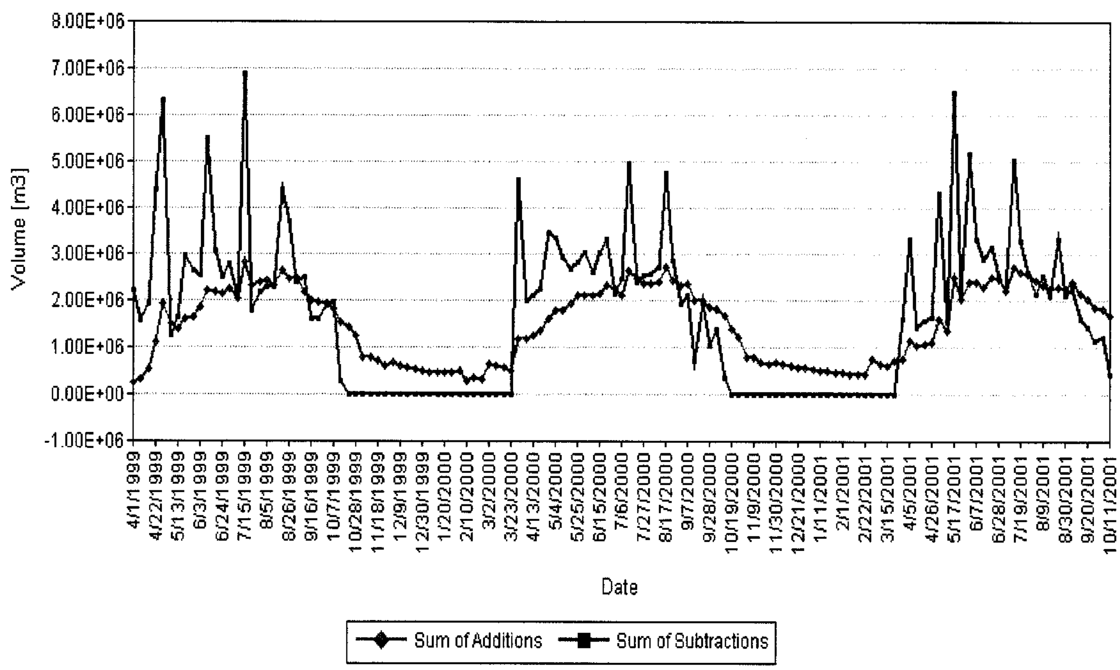


Figure 7.39 – Aquifer water balance change from the baseline conditions in Rech50 alternative

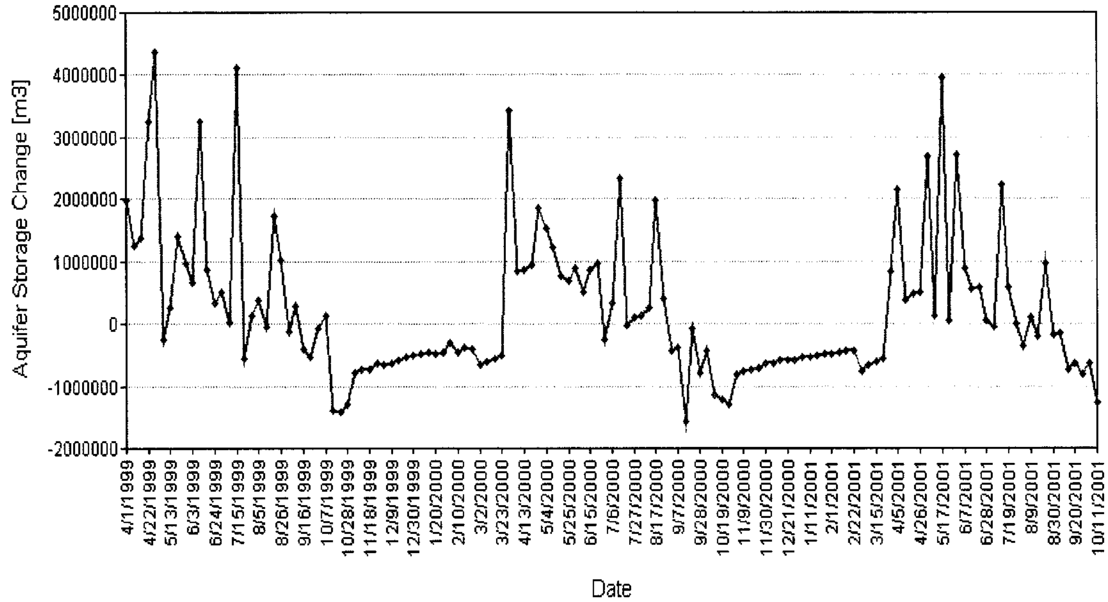


Figure 7.40 – MODFLOW Aquifer storage change from the baseline storage in Rech50 alternative

The true water savings could occur from the portion of the reduced upflux amounts located under fallowed and naturally-vegetated areas. In this alternative simulation, the simulated total upflux reduction is 25.1x10^6 m^3 (20,348 acre-ft), representing approximately 10% of the modeled recharge reduction. Assuming a uniform upflux reduction over all the fields in the modeled area, a quick approximation of the potential water saved under this scenario as a function of the aquifer recharge reduction volume can be performed using the percent of fallow fields for a given year. As an example for 2003, the percent of the fallow fields in the modeled area reaches almost 50% of the fields, potentially representing a 5% [1/2*(10%)] of the areal recharge reduction as real water savings as consequence of the alternative implementation. Current studies in the Arkansas Valley are attempting to better quantify ET from fallow and naturally-vegetated fields for better approximating actual water saved from the reduced diversion due to lowering of the water table and associated reduction in upflux to ET. Most likely, the implementation of these kinds of alternatives will drive the system to a new long-term equilibrium that might include less aquifer storage than the baseline equilibrium state. In conclusion, the simulated results for this management alternative reflect the best possible improvements in the system quality and feasibility because of aquifer storage water made available to the surface system for dilution and for meeting downstream water obligations.

In summary, the groundwater modeling results of the 50 percent reduction in areal recharge alternative reveal changes in all components of the MODFLOW-MT3DMS flow budget, even though this alternative only directly impacts the aquifer recharge. Changing the aquifer dynamics by lowering the water table has the consequence of increasing canal seepage, reducing upflux, and reducing aquifer storage. As expected, return flows are shown to decrease, but in smaller amounts than the reduction in recharge; i.e., the non-diverted water exceeds the reduction in return flows.

The canal seepage change observed in this recharge reduction alternative simulation exposes an inconsistency in the basin-scale modeling since the *LAR GeoDSS* alternative manager takes into account only changes in the modeling system explicitly stated in the alternative. Future refinements of the modeling system need to correct the canal seepage change as a consequence of indirect impacts of the management alternatives. In the current system, the assumed canal seepage affects the ANN explanatory variables. However, errors introduced by neglecting changes in canal seepage are expected to be minimal because the ANN training is based on the originally assumed seepage amounts (i.e., first pass results) that did not include the changes in seepage. The ANN is trained with a canal seepage explanatory variable that does not include the indirect adjustment. That is, since the ANN is trained to duplicate the MODFLOW-MT3DMS modeled return flows that include all components of the flow budget, the stream-aquifer interaction predictions are expected to have less error by using the originally assumed canal seepage as a fraction of the diversion. A more significant error can be expected in the diversion reduction because the increase in canal seepage requires additional diversions to overcome these additional losses. Therefore, the modeled diversion reduction is actually greater than what it should actually be.

SUMMARY OF MANAGEMENT ALTERNATIVES MODELING

Analysis of the MODFLOW-MT3DMS modeling results reveals the interrelationship between the modeling components, enhances understanding of the management alternative modeling results, and reinforces confidence in the powerful stream-aquifer representation methodology implemented in *LAR GeoDSS*. Groundwater modeling analysis of the *Rech50* alternative shows additional water available to the surface system during the basin scale simulation of the management alternatives due to aquifer depletion without representing water savings to the system. However, there is a portion of that water actually saved by reducing upflux to ET on fallowed fields and naturally-vegetated areas.

The simulation of management alternatives that were not included in the MODFLOW-MT3DMS modeled set (e.g., *new_Rech50Seep50*) illustrates the power of the implemented modeling system. The *LAR GeoDSS* modeling system is able to simulate these new management alternatives using the ANN-based stream-aquifer interaction model and the Scenario Manager functionality. Return flow predictions for these new management alternatives are checked against MODFLOW-MT3DMS modeling results of alternatives with similar characteristics, demonstrating the reasonable *LAR GeoDSS* prediction.

The results for operational Mode B demonstrate the importance of exploiting flexibility in the reservoir operations in pursuit of implementation of the management alternatives. The operational Mode A, with limited changes in the reservoir operation, shows that most of the alternatives require at least a minimum adjustment to the reservoir operation in order to be feasible. The most effective improvements in the river water quality are found in Mode B, where additional water stored at the end of the simulation indicates a greater potential to improve water quality in the system by releasing the additional water in patterns designed to meet water quality targets. In this case, additional releases during the irrigation season might have the best impact on agricultural activities by applying better quality water to the fields, with the off-season low flows potentially more concentrated. In terms of water quality improvements and reservoir storage usage, the results presented in the Mode B simulations can be considered as the worst case scenario for each of the alternatives. In the water quality aspect, the additional water stored in the reservoir should be released to further improve the simulated concentrations. The simulated reservoir storage is the maximum required since strategic releases distributed over the simulation period will reduce the storage requirements.

The inclusion of economic aspects of implementation of the proposed alternatives could enhance the analysis and the ranking of alternatives for future selection of those alternatives best suited for salinity and waterlogging remediation, river water quality enhancement, and water conservation. The study presented herein demonstrates the type of comparative analysis that is possible with the *LAR GeoDSS* modeling system and the ability to screen management alternatives that are going to be more difficult to implement because of violation of water rights and river compact or because implementation requires significant modifications to the water law and reservoir operation rules. It is important to point out that the surface drainage improvement alternatives do not consider the addition of the drained water to the surface system; therefore, some of these alternatives that violate water law could still be implemented if more detail modeling of the drained volumes is incorporated.

CHAPTER 8

SUMMARY AND CONCLUSIONS

River GeoDSS, a spatial-decision support system, is designed and developed to assist in the increasingly difficult task of decision making in river basins when simultaneously considering water quantity and quality, along with legal, operational and administrative aspects. The *River GeoDSS* employs state-of-the-art technology, combining existing models and tools (MODSIM, MODFLOW-MT3DMS, MATLAB, ANN and ArcGIS) and creating modules and interfaces to provide the user with a robust decision support environment. The unique feature of *River GeoDSS* is seamlessly combining its modeling and data subsystems in a powerful and fully-featured GIS interface for water quantity and quality conjunctive surface and groundwater modeling, promoting understanding of water system behavior and facilitating the analysis and comparison of water management alternatives.

River GeoDSS integration with native GIS layers allows use of the USGS National Hydrography Dataset (NHD) networks or existing geo-representations of the system to speed up the construction of the modeling system for the *River GeoDSS*. The capability of the *River GeoDSS* to automate many modeling tasks greatly facilitates system calibration and simulation of complex river basin systems. In addition, implementation of the *River GeoDSS* inside the popular ArcGIS environment avoids the need to learn a new interface to create, manipulate and display the modeling system, making the *River GeoDSS* attractive to new users already familiar with ArcGIS.

River GeoDSS is designed with a core functionality that can be used in any open-channel water system, but with the capability for customization to accommodate particular needs, data sources, analysis, and execution modes (taking advantage of MODSIM customization features). The *River GeoDSS* is a generalized river basin modeling tool, thereby providing a framework with basic tools, modules and methodologies to perform geo-referenced conjunctive surface and groundwater basin modeling. Problem-specific customization allows particular needs, data processing and questions to be addressed for each modeled system. It is believed that the *River GeoDSS* customized applications operating within ArcMap make it appealing, useful and easy to use/adopt by decision makers with a wide range of backgrounds. The *River GeoDSS* main components include Geo-MODSIM, Geo-MODFLOW, an ANN module, the Water Quality Module (WQM), and a set of core interfaces and tools.

Geo-MODSIM extends the MODSIM functionality to ArcGIS by separating the links in streams and canals and implementing gauging station nodes. Use of the ArcGIS geometric network to represent the stream system network allows entering and storing information (e.g., terminal interface characteristics, return flow types and flags, capacities, costs, and priorities) in the GIS objects for robust modeling. This enhanced network representation facilitates network transformations for automatic calibration and simulation operations, as well as special modeling features such as the ANN-based stream-aquifer interaction. Geo-MODSIM provides the core functionality to (1) build any MODSIM network from a functional geometric network, (2) access MODSIM dialogs to enter, edit and visualize model data, and (3) display model output in the GIS interface in an object-oriented and spatially distributed fashion.

Geo-MODFLOW is a *River GeoDSS* tool to manipulate and display MODFLOW-MT3DMS modeling results in ArcGIS. The tool geo-references the model grid and links it with the binary output files, providing spatial-query access of the groundwater flow and water quality modeling results. Geo-MODFLOW allows summarizing and visualizing the groundwater flow budget components and salt loading (concentrations) results for any point, line(s) or polygon(s) in ArcMap, as well as programmatically generating training variables for the ANN Module.

The ANN module uses trained ANNs with different structures to be simulated in the *River GeoDSS* to assist in the modeling of complex phenomena. The ANN module relies on external files containing all the trained ANN information to perform predictions. The ANN module provides a set of MATLAB-based custom interfaces to perform ANN training including: (1) data pre-processing, (2) selection of training options, (3) sequential training for semi-automatic structure and parameter selection, (4) post-processing, (5) training results analysis, and (6) trained ANN export for *River GeoDSS* usage. The ANN module is implemented in the *LAR GeoDSS* for stream-aquifer interaction modeling as an alternative to traditional approaches for basin-scale modeling of conjunctive use of groundwater and surface water modeling. In addition, the ANN module is also applied to reservoir salt transport modeling for predicting the salt load downstream of a reservoir in the evaluation of water management alternatives.

The WQM performs conservative dissolved constituent routing in the *River GeoDSS* modeled system. The module includes (1) general interfaces for data entry, visualization and basic regression functionality to predict concentration as a function of flow, (2) a MODSIM network tracing algorithm to determine the network calculation order from upstream to downstream, (3) the water constituent routing tool that accommodates ANN module predictions and integrates with MODSIM for simultaneous water quantity and quality modeling, and (4) storage and display of the module results. WQM stores data in network-based databases, thereby enhancing data sharing and portability for analysis of improved water management alternatives modeling.

The *River GeoDSS* Simulation Scenarios Manager provides files management capabilities and handling of the graphical/tabular comparison of results between the various simulated scenarios. In addition, customized application of the scenario manager allows setting network preferences and operational characteristics to simulate "what if" water management simulation scenarios (e.g., those examined with the *LAR GeoDSS*). The *River GeoDSS* modeling tools simplify the water quantity and quality network calibration, as well as the simulation processes making use of the calibration results.

The seamless integration of the *River GeoDSS* components in both calibration and simulation modes allows state-of-the-art modeling of conjunctive use of groundwater and surface water quantity and quality. The *River GeoDSS* is demonstrated by application to the LARV in Colorado with focus on screening of improved water management alternatives. The *LAR GeoDSS* provides a set of custom tools to build the modeling system from the available data, calibrate the water quantity and quality modules, and simulate "what if" simulation scenarios for evaluation of improved water management alternatives in the LARV. The network calibration automatically computes local gains and losses representing unmeasured components of the river system. These gains and losses are incorporated into the simulation by assuming the same underlying hydrological conditions to evaluate system response to changes in operational rules, agricultural practices, and infrastructure improvements. The water quality calibration enables computation of unknown salt concentrations to match as closely as possible the measured concentrations at selected control points. The unknown concentrations are constrained to maximum and minimum field-observed values in the monitored regions, and the ANN is used to predict salt loading to the river from the aquifer as a known water quality component. Unfortunately, assigning TDS concentrations within the allowed range to inflows lacking measured concentrations limits the ability to control the downstream reach concentration and to match measured concentrations at several control points in the system. The baseline simulation is used to compare relative changes in concentrations during simulation of the water management alternatives, which reduces the impact of the constrained water quality calibration.

The comparative analysis of regional-scale-developed water management alternatives implemented at a basin scale was performed for the LARV using two river system operational modes. The results show that small adjustments and flexibility in the reservoir operation policy are required for implementation of most of the alternatives. In addition, the ability to control the storage and release of additional flows generated by the improved water management alternatives provides noticeable improvement in the overall water quality of the system. This is particularly true when additional water is stored in the reservoirs at the end of the simulation period, since this represents water that could be used during the year to further improve water quality in the system by diluting flows released for beneficial uses. In this ideal operation, impacts on the reservoir operation policy could be less than those presented herein, since water will be released during the year when needed, rather than stored over the length of the simulation period. Further investigation is required to determine if it would be possible to amend the Arkansas River Compact allowing a new account to be created in John Martin reservoir to store water generated by the improvement alternatives implementation, regulate it to improve the water quality in the entire system, and indirectly increase flows at the state line.

The ANN used in the *LAR GeoDSS* for stream-aquifer interaction modeling is trained on a regional-scale groundwater flow and salt transport numerical model to recognize patterns between system state changes (i.e., stresses) in the surrounding areas to the modeled interface and the stream-aquifer interaction. The extracted relationships are applied to predict interactions at the stream-aquifer interface in neighboring non-modeled areas. This ANN modeling approach indirectly captures all aspects modeled in the finite difference groundwater model, including detailed non-saturated zone water and salt transport modeling. In this sense, the introduced methodology does not require simplified assumptions or lumped parameters that are required within many basin-scale return flow prediction methods. In addition, the ANN is trained based on historical stress combinations (i.e., weekly pumping combined with canal seepage and areal recharge) and calibrated aquifer responses. Therefore, the system states used for ANN training are realistic and physically based. The ANN training includes simulated responses from the management alternative groundwater simulations that enhance its ability to predict stream-aquifer interactions resulting from changes to the historical stresses.

ANN prediction from two different system operations showed good agreement between the prediction and the MODFLOW-MT3DMS modeled net return flow and salt loadings for several grouping areas and scenarios. The small ratio between the number of cases used in training and those used in testing indicates that the ANN has developed strong relationships between the explanatory variables and the predicted variables by predicting with good accuracy a larger number of cases outside of the training datasets. The *LAR GeoDSS* stream-aquifer interface modeling at the basin scale approximates "reasonable" return flow and salt load values according to historical surface system observable characteristics. Evaluation and analysis of flow predictions over the improved water management scenarios indicate their consistency with respect to the baseline conditions. Although the predicted TDS concentrations show discrepancies between the baseline as modeled in MODFLOW-MT3DMS and the *LAR GeoDSS*, the small magnitude of the percent error is not expected to be significant in the overall process of screening alternatives. The stream-aquifer modeling approach introduced herein reveals a promising alternative path for basin scale conjunctive surface groundwater modeling, especially in the evaluation of "what if" scenarios.

As found in the literature reviewed, the ANN is positively influenced by the "memory" provided by the usage of previous observations as explanatory variables. The *LAR GeoDSS* stream-aquifer interaction modeling using the ANN is tested though simulation, where the ANN predictions are used as previous observation explanatory variables in the prediction. In this situation, there is the possibility of jeopardizing the prediction by sequential accumulation of prediction errors. The ANN priming to find a good starting prediction point seems to be a key instrument in developing stable ANN predictions. Even though larger errors are observed during simulation than during the ANN testing, the overall predictions in the simulation seem to be in agreement with the order of magnitude and distribution of the MODFLOW-MT3DMS modeled data. Comparison of the aquifer net return flows and the total net gains from surface water measurements suggests an over-prediction tendency in the *LAR GeoDSS* ANN predictions. Finally, embedding the ANN within the basin scale decision tool eliminates the computational burden of directly incorporating realistic finite-difference models such as MODFLOW-MT3DMS over the entire basin.

The screening of water management alternatives using the *LAR GeoDSS* leads to identification of infeasible management alternatives based on exhaustion of water in the reservoirs at the end of the simulation, significant water shortages, and Arkansas River Compact violation. Feasible water management alternatives with the larger reduction in areal recharge and canal seepage in the operational mode B, such as *Rech80Seep90*, *Rech80Seep90Drain50* and *Rech90*, showed the largest potential to improve conditions in the basin. The improvement potential is evaluated based on amount of water stored above historical levels in the reservoirs, and in reduction in TDS concentrations at diversions and at the Kansas-Colorado state line.

In summary, the *LAR GeoDSS* is a unique decision support tool for evaluating the benefits and feasibility of regional-scale improved water management alternatives, in which the scenario approach applied here provides a solid framework for comparison of water management alternatives, thereby reducing the effects of calibration and simulation errors in the analysis. The *LAR GeoDSS* is a prototype system that could provide the basis for the proposed State of Colorado Arkansas River basin decision support system.

FUTURE IMPROVEMENTS AND RESEARCH IDEAS

RIVER GEODSS ENVIRONMENT

Implementation of the *River GeoDSS* in Other GIS Environments

Although, ArcGIS™ is the most widely used GIS package in the world, the need to acquire expensive licenses is still an obstacle for targeted *River GeoDSS* users with little experience in GIS. The cost of the ArcView™ as a minimum requirement for GIS functionality in the *River GeoDSS* may also be too high for many users. In these cases, it would be ideal to support the *River GeoDSS* under different GIS platforms with low cost licensing requirements. A strong candidate is *MapWindow*™, an open source programmable GIS system (http://www.mapwindow.com/) which has an actively growing user community. The implementation can be designed to use the underlying files and modules currently utilized in the *River GeoDSS*, allowing a *River GeoDSS* project to be used across GIS platforms. The *MapWindow* GIS environment does not require a purchased license as the ESRI products do.

River GeoDSS Online Interface

An online version of the *River GeoDSS* would facilitate its accessibility for a larger group of interested users. A *River GeoDSS* viewer can be designed to provide decision making support, information, and enhanced understanding of a river basin. In addition, feedback from a larger group of beta users could provide a substantial contribution in guiding future enhancements and tool developments.

Water Quality Module Expansion

The current *River GeoDSS* Water Quality Module only deals with routing of conservative solutes, and is specifically designed for salt transport modeling only. Future work should expand the water quality modeling capabilities, building on the current structure and tracing utilities, to implement chemical reactions and other processes throughout the network for potentially non-conservative constituents. Complex water quality modeling could also be accomplished by coupling the *River GeoDSS* with link-based water quality models such as QUAL2E.

River GeoDSS Data-Management Tool Improvement and Time Series Database Improvement

Improvements to the core *River GeoDSS* functionality can include a data import tool that implements the most common sources of data, e.g., USGS and CDWR. The *River GeoDSS* data could be updated using data available on USGS web links and CDWR databases. Dynamic linkage with data sources could automate the population of time series, water rights, and even system characteristics. This automation would not require local management of data and could facilitate *River GeoDSS* usage in the future. The structure of the time series database can be revisited to make its implementation easier and dynamic for future *River GeoDSSs*. Use of HydroIDs is cumbersome, and better results could be obtained using the native HydroCode that is used in the downloaded data. New technologies such as the Network Common Data Form (*NetCDF*) supported in ArcGIS 9.2

should be explored as alternatives to efficiently managing time series data in GIS-based systems.

Implementation of Time-Variant Water Rights Tool

Water rights change over time due to abandonment, transfers, sales, exchanges, etc. The current water rights utility processes the transactions to bring them up to date transactions in the river basin simulation. A time-variant water rights analysis tool is proposed for accurately performing long-term historical simulations where water rights might have been active at some point but are currently inactive. The tool would require the use of water rights time series data, which are not currently handled by the MODSIM water rights utility.

Improvement in the *River GeoDSS* Network Update

At this stage, the *River GeoDSS* includes an inadequate algorithm for capturing changes in network topology in the geometric network and translating those changes into the MODSIM network. It is proposed that the algorithm be updated to allow capturing changes in the system topology and accommodating these changes in the MODSIM modeling system without the need to regenerate the network.

LOWER ARKANSAS RIVER GEODSS

Stream-Aquifer Interaction Modeling Enhancement

Additional passes of the simulation-training procedure could be implemented to refine the simulation-dependent explanatory variables such as canal diversions and river flows, as well as including surface water quality related explanatory variables that indirectly provide information about salt loadings to the soil from irrigation activities. Location of the prediction within the basin should be accounted for since noticeable salt concentration changes are registered from upstream to downstream. Additional explanatory variables can be introduced that directly account for relative changes in the original explanatory variables between previous and current time steps, providing additional "memory" to the prediction process; however, difficulties related to the initial conditions for simulation are anticipated. Incorporation of other variables related to alluvial aquifer properties, such as hydraulic conductivity and aquifer thickness, should be considered.

Improvement of performance in predicting return flow and TDS concentration in the tributaries should be explored in future improvements of the *LAR GeoDSS*. Better performance could be achieved by incorporating additional or new explanatory variables that could capture system stress changes in area-buffers around the tributaries, building area-buffers for tributaries in a fashion similar to that for the main stem in the current explanatory variables processing. In addition, defining individual grouping areas around each tributary might improve the resolution of the tributaries predictions, especially for current cases where different size tributaries are located in the same grouping area.

Introducing system stresses from upstream of the grouping area could provide additional information to explain return flows. This could be achieved by using the already calculated explanatory variables or defining new buffers that partially cover the neighboring region of the upstream grouping area. Additional improvements to the stream-aquifer interaction could be achieved by developing additional explanatory variables to capture quality aspects of the basin and the aquifer.

It is believed that additional MODFLOW-MT3DMS modeled areas (downstream of John Martin Reservoir regional model) will greatly enhance the ANN training dataset by providing a wider range of geometries and therefore historical conditions and aquifer responses. Another enrichment of the training dataset can be achieved by extending the modeled time period of the current MODFLOW-MT3DMS modeled area by providing responses under different hydrologic and climatic regimes. Tributary return flow and salt load predictions could be improved by adding explanatory variables that provide information regarding the size of the tributary and frequency of flows.

Since the ANN is duplicating the MODFLOW-MT3DMS response, improvements in groundwater model calibration, especially improvements in the surface flow calibration, should consequentially reduce the uncertainty in the evaluation of water management alternatives. Improvements to the MODFLOW-MT3DMS model such as the use of NEXRAD spatial precipitation estimates can greatly enhance the information provided to the ANN by these precipitation explanatory variables. Currently, there is only one available pumping scenario modeled in MODFLOW-MT3DMS. Additional modeling of vertical drainage scenarios should provide the ANN with better foundation to make consistent predictions of this scenario type.

Groundwater Modeling Improvement Using Surface Water Modeling

A dynamic interaction between the MODFLOW-MT3DMS models and *LAR GeoDSS* could be implemented to provide the modeler with tools to check modeled return flows against the unmeasured gains and losses computed in the surface system water balance between gauging stations, allowing a more refined MODFLOW-MT3DMS flow calibration. In addition, *LAR GeoDSS* simulated TDS concentration at water diversion points can be used to improve the MODFLOW-MT3DMS simulation, providing more realistic estimates of the salt applied to the soils by irrigation within the water management alternatives.

Management Alternatives Modeling Improvements

Modeling the management alternatives could be improved for more accurate evaluation of the alternatives in the following aspects.

Refined Description of Areal Aquifer Recharge as Affected by Irrigation Application Efficiency

Application efficiency could be represented as a function of the canal command area, location, time or available flow. A more flexible and varied application efficiency is proposed to be implemented in the *LAR GeoDSS*, where the efficiency term could be associated with each canal command area, thereby affecting refined reduction in areal recharge to the aquifer.

Reservoir Layer Balancing Improvements

The reservoir layers used to model system storage should be improved for more realistic simulations. The current storage zones or layers defined for John Martin Reservoir and Pueblo reservoir result in operations with extremely low volumes to be stored in John Martin Reservoir due to the layers design to store water as high in the system as possible. More realistic reservoir operational policies can be custom-coded into MODSIM to handle this situation. Interviewing the reservoir operators could guide improved representation of the operating rules towards more realistic simulations.

Refinement of Sub-Surface Drainage Alternative Modeling

The sub-surface drainage alternative modeling should be improved for better prediction of drainage water back to the river system. The drained volume is returned to the surface water system more rapidly than if it travels through the aquifer porous media. The improved prediction of drainage water will allow better evaluation of the performance and feasibility of these alternatives. The existing stream-aquifer interaction ANN could be enhanced, or a similar modeling approach used, to predict drainage water for the groundwater grouping areas. The drainage water can be distributed among the river nodes in the grouping areas in a similar fashion to the vertical drainage scenario.

ANN Improved management alternative modeling

ANNs can be used to improve predictions of modeling components that directly affect system water availability in the basin scale modeling such as canal seepage estimation and actual irrigation induced aquifer recharge.

Improved Estimation of Areal Aquifer Recharge

Estimation of areal aquifer recharge from overirrigation could be refined by using the MODFLOW-MT3DMS output to train an ANN that predicts aquifer recharge based on the system state and the management scenario characteristics, enabling the ability to predict more accurately the areal aquifer recharge volume, that is currently calculated as a function of the canal diversion.

Improved Seepage Prediction

Indirect changes in canal seepage caused by other management alternative components can be captured from the MODFLOW-MT3DMS output. An ANN-based method is proposed to model the changes in seepage during the detailed MODFLOW-MT3DMS modeling. The ANN could predict canal losses for simulation of both the baseline and those management alternatives that do not include explicit calculation of seepage reduction.

Diversion Reduction Algorithm Improvement

Improvement in the *Simulation Scenario Manager* tool that adjusts system water demands is proposed. Since some of the improved water management scenarios specify increased efficiency in water usage, it is likely that less water will be needed from storage contracts before direct flow diversions are reduced. Since the storage contracts are modeled as high priority links, historical diversions from storage contracts should be reduced at the same time that node water demands are reduced.

Time Series Improvements

An improvement in the Geo-MODSIM time series management module would involve moving MODSIM time series data to a database management system that provides more flexibility, control, and tools to analyze and enter data into the MODSIM objects. The time series database implemented for the water quality module could be expanded to achieve this goal. In addition, linkage or usage of third party time series managers should be explored to enhance flexibility and attract more users. Some available time series managers that could be considered include: the DHI Temporal Analyst (http://www.dhigroup.com/Software/WaterResources/TemporalAnalyst.aspx) and the U.S. Army Corps of Engineers (HEC-DSS) time series database management systems.

Finally, time series processing tools should be implemented in the *LAR GeoDSS* for filling gaps in data, providing statistical and forecasting information. This functionality could be added by linking *LAR GeoDSS* with existing tools such as CSU-SAMS (Sveinsson et al. 2003).

Improved Modeling of Water Carrier Structures

An additional implementation is required to discourage usage of canal diverted flows by in-canal demands, forcing the in-canal demands to fully utilize the diversion structure bypass link (described in Chapter 6) as their water supply. This implementation will require changes to the network cost structure and a custom code to transform the terminal interface modeling from low priority sinks to high priority demands so that they are able to retain the diverted flows in the canal links until the end of the canal.

Canal Seepage Losses Simulation Improvements

The original assumption of a basin-wide seepage loss reduction coefficient should be relaxed by including detailed data from the canal seepage loss field studies, where available. This process might require including more complex seepage functions that are conditioned on canal flow rates, pre-existing conditions, and soil profile characteristics. The *LAR GeoDSS* data-model and spatial representation of the system will be extremely useful for this implementation. Canal seepage characteristics could be defined at high resolution (by link) and combined to be included in the basin water demand calculations. These algorithmic improvements can lead to better model alternatives for simulating the impacts of lining sections of canal systems. Since the return flows are spatially affected by the lined sections, the data-model could be updated to hold seepage loss reduction coefficients for each link in the system where changes in seepage characteristics are introduced. The algorithm to capture seepage-related explanatory variables will have to be improved in order to accommodate the link-based seepage characteristics.

Unmeasured Tributary Flow Estimation

It is believed that unmeasured tributary flows are a large fraction of the total unknown gains to the system. Estimation of tributary flows requires a robust predictor since the phenomenon is intermittent and depends upon surface runoff as well as upon groundwater contributions. An ANN-based model using NEXRAD spatial precipitation, other system stresses and physical characteristics of the sub-watershed as explanatory variables could provide valuable predictions reducing the unknown gains in calibration. Tributaries with measured flows can be used for training and testing to develop predicting models for other tributaries. Tributaries could be grouped by size and similar characteristics to guide the flow predictions. Challenges are expected for modeling small tributaries, usually with sparsely-measured data, that will not have a rich training and testing dataset.

Optimal System Operation to Meet Water Quality Goals

Reservoir operations could be optimized to meet water demands and to minimize deviations from water quality targets. Using an iterative approach, the system could be modeled by the *LAR GeoDSS* and optimized with the CSUDP dynamic programming algorithm until convergence to a solution. The optimization results would take into account the conjunctive use of water in the basin, as currently modeled in *LAR GeoDSS*. Successful linkage of MODSIM and CSUDP for including dynamic programming in optimal reservoir operation design (Triana and Labadie 2000; Uematsu 2007) can be used as platform for this improvement.

System Operation under Restricted Operational Policies

Additional simulations of the system assuming restricted usage of a particular in-stream reservoir could be useful in negotiation of a win-win situation for all parties involved in the

Arkansas River Valley operation. For example, assuming that the Arkansas River Compact cannot be modified, a system simulation that maintains historical volumes to the compact accounts provides information about the feasibility and expected improvements if only Pueblo Reservoir is available for regulating water generated by the management alternatives implementation.

Detailed Modeling of Complex Water Storage Operations

Initially, a custom tool can be implemented to summarize storage water use for reservoir water accounting. This interface would be based on information stored in the *F* field of the CDWR diversion records database, which indicates the source of the storage account. The MODSIM output can be combined with the storage owner modeling links to generate reports of storage water use per owner.

The modeling of storage accounts can be implemented to allocate supplemental water for users holding both natural flow water rights and storage account ownerships. It is recommended that improved diversion modeling be implemented whereby diversion nodes could be bypassed to enable storage of water in the off-stream reservoirs. Initially, the carrier links could be set with upper bounds corresponding to the historical diversions. Stored water should be allocated to the storage ownerships using storage accounting mechanisms available in MODSIM.

Refining Water Quality Modeling

It is highly desired to improve the TDS concentration predictions for those periods where there is a lack of measured concentration data. A more robust method should be implemented to improve the prediction performance by regionalizing the water quality regression equations to predict concentrations at stations with limited numbers of observations. Alternatively, an ANN could be trained with sets of explanatory variables that capture more conditions for predicting concentrations. This implementation could be investigated by basin, region, or individual stations.

Use of equations for converting EC to TDS can be improved by implementing the use of zonal equations to import the water quality data. New relationships could be derived for specific points in the basin where more accurate TDS values are needed (e.g., water quality at the Colorado-Kansas state line).

Efforts should be made to incorporate other solutes of interest into the model, such as Se and U. This will require the inclusion of these constituents in the MODFLOW-MT3DMS model and associated ANN.

Extending the Modeling to the Arkansas River Head Waters

The current extent of the *LAR GeoDSS* could be expanded to include the portion of the Arkansas River Basin in Colorado upstream of Pueblo Reservoir. This process will require development of additional groundwater models or methodologies to implement conjunctive use modeling in areas with significant change in system characteristics. This improvement will allow a comprehensive basin-wide management analysis with improved conditions upstream directly influencing the initial environmental conditions downstream and also comprehensive analysis of the water rights in the basin for development of operational strategies aimed toward implementation of the water management alternatives.

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APPENDIX I

ANN TRAINING DATASET DESCRIPTION

EXPLANATORY VARIABLES

The ANN explanatory variables described in this appendix were designed to represent the system state and provide the ANN with pertinent information about the current state and magnitude of stresses change with respect to previous states. Explanatory variables are totalized by grouping areas and depending on its nature further summarized by area-buffer. In the following reference, the internal *River GeoDSS* keyword for the variables is supplied in parenthesis for each explanatory variable. Keywords were used in the training dataset, MATLAB training and testing tools, as well as in the *River GeoDSS* ANN module to consistently keep track of the variables. The examples provided in this section relate to the ANN-based stream-aquifer interaction modeling in the LARV. The results of the explanatory variables processing is stored in the *buffers* database, which is a MS-Access database that combines geo-referenced layers and data tables to store the processed explanatory variables and processing support information.

Grouping Area-Based

These explanatory variables are extracted per grouping area. They provide information related to the main stream segment and the overall modeling conditions.

Main Stream Length (StreamLengthArk)

This variable contains the grouping area main stream length in kilometers. For most of the modeling areas in the Arkansas Valley, it is 15 km except the areas intercepting John Martin Reservoir where the main stream is submerged and the first one that extends longer to completely cover the irrigated valley (Figure I-1).

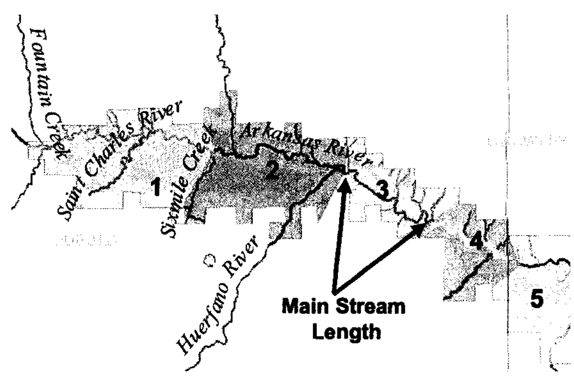

Figure I-1 – Main stream length example in upstream grouping areas

Tributary Stream Length (StreamLengthTrib)

This variable indicates the total length of tributary lines in the grouping area in kilometers.

Average River Elevation (AveRiverElev)

The groundwater flow analysis (Chapter 4 – *Spatial Variable Grouping*) exhibits the importance of the relationship between the elevation of water bodies, canals and the river elevation in the magnitude and direction of the flows. This explanatory variable measures the average elevation in the main river segment in the grouping area. This variable is calculated using the GIS Zonal Statistics function for the main stream line on the USGS Digital Elevation Model (DEM).

River Flow Indicator (RiverFlow)

The average flow in the river and tributaries links that are flagged for ANN return is computed as indicator of flow state in the grouping area. This value is computed with the assistance of the table *RiverLinksBufferID* (located in the data-model) that contains the links and corresponding grouping area's IDs with a place holder for a single flow value that is updated at run time for each time step. The average calculation includes flow of both the links completely contained inside the grouping area and links intersecting the boundaries of the grouping area.

Pumping Increase Indicator (PercPumped)

This explanatory variable reflects the percent of pumping increased, which is used only in vertical drainage alternatives.

Subsurface Drainage Indicator (DrainSpc)

An indicator is included to provide the ANN with information about the spacing density in sub-surface improvement management alternatives. The drain spacing value, used to identify the management scenario, is entered in the ANN training dataset to capture the effect of drainage improvement in the stream-aquifer interaction modeling. The variable doesn't take into account the percent of the irrigated fields that are improved.

Area-buffer-Based

The following explanatory variables are extracted per area-buffer; an explanatory variable is created in the training dataset for each area-buffer

Area-Buffer Area (BufArea_)

This variable consists of the total area of the area-buffer in square kilometers (km^2). The variable includes all polygons in the area-buffer even if they are not physically connected (see Figure I-2).

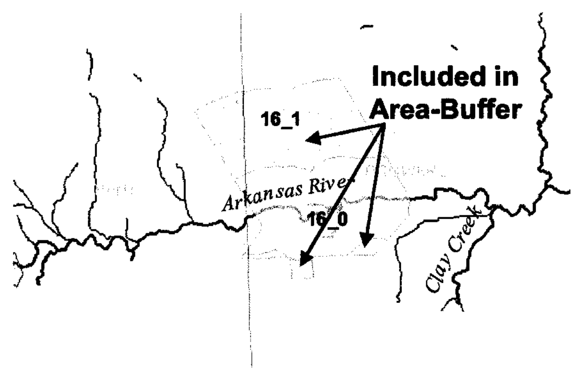

Figure I-2 – Area-buffers configuration in grouping area 16

Average Terrain Elevation (AveElev_)

The average elevation of the area-buffers terrain is used to calculate the ANN explanatory variable. The average elevation is computed using GIS-Zonal Statistics applied on the DEM for the area-buffer polygons. The processed averaged elevations are stored in the database table *AverageElev*. The explanatory variable *AveElev_b* is calculated, for area-buffer *b*, as the difference between the average elevation in the area-buffer (E_b) and the average elevation in the main river[b] (RE_i) for grouping area *i* normalized by the river elevation.

$$AveElev\_b = \frac{E_b - RE_i}{RE_i}$$

[b] Explanatory Variable *AveRiverElev* for area-buffer *b*.

Water Bodies Areas (WBArea_)

This explanatory variable is created to represent the extension of the surface water accumulation in the area-buffer. GIS geo-processing tools are used to intersect the polygons representing water bodies and area-buffers. The total area of polygons (or part of polygons) inside the area-buffers are summarized as the explanatory variable. The value itself provides an idea of the extent of the water bodies and the grouping in area-buffers provides insight on the location of them respect the river system. The results are compiled in the *BWBodies* prefixed tables in the *buffers database.*

Water Bodies Elevation (WBElev_)

The elevation of the water bodies with respect to the mean sea level is calculated based on the DEM using the GIS-Zonal Statistics function. The average values are summarized in the database table *BWBodiesElev.* This explanatory variable captures the average elevation of the water bodies in the area-buffer with respect to the river elevation. The explanatory variable is computed as the difference between the average water bodies elevation (WBE_b) in the area-buffer b minus the average elevation of the river (RE_i) in grouping area i divided by the average elevation in the river (RE_i).

$$WBElev\_b = \frac{WBE_b - RE_i}{RE_i} \tag{I.1}$$

Diversion (AveDiversion_)

An explanatory variable is created to provide information of the magnitude of the diversion water applied to the irrigated fields in the area-buffers. The diversion per area-buffer (D_b) is calculated as the combination of the fractions of the diversions proportional to their area-buffer irrigated area with respect their total irrigated area.

$$D_b = \sum_{C_b} D_c \, {A_{b,c}}/{A_c} \tag{I.2}$$

where, D_c = the diversion of canal c. C_b = the set of canals that irrigate fields in buffer b. $A_{b,c}$ = the area irrigated by canal c in buffer b, and A_c = the total area irrigated by canal c.

Precipitation (Precip_)

Spatially-varied precipitation is processed at weekly time steps for the *River GeoDSS* use. The spatially-varied (raster) maps can be generated either from NEXRAD processed rainfall or using spatial interpolation from the point-measurement data (CoAgMet and NWS stations). The *River GeoDSS* implements a tool using GIS functions that allows processing point-measured variables to generate climate variable raster maps using the inverse distance method. The weekly precipitation is stored in a database that is accessed for both training and simulation. GIS Spatial Analyst functions are used to create weekly summary tables with the mean precipitation per area-buffer. The table name uses a user-defined prefix and the beginning of time step date (*ddmmYY*). Summary tables are reliant on area-buffers and time step, alteration in any of these elements requires re-generation of the precipitation summary tables. For example, if ANN training time steps are shifted from the simulation time steps, different tables will need to be generated for training and simulation.

Canals (Canals_)

The length of canals in the area-buffer will bring in an indicator of the amount of potential seepage interfaces and their location with respect to the main stream. This explanatory variable is computed clipping the canal lines by area-buffers and totalizing all the lengths.

Canal Elevation (BCanalsElev_)

In the groundwater regional-scale modeling (Burkhalter and Gates 2005; Burkhalter and Gates 2006), the relationship between the canals stage and water table depth shows a significant influence in the modeling results. At basin scale, we can approximate the canal stage using the DEM-derived canal elevation respect to the mean sea level. This explanatory variable captures the relationship between the average elevation of all canal lines in the area-buffer with respect to the average elevation in the river. The variable is computed using GIS-Spatial Analyst tools and stored in the table *BCanalsElev*. The explanatory variable is computed as the difference between the average canals elevation (CE_b) in the area-buffer b minus the average elevation in the river (RE_i) in grouping area i divided by the average river elevation (RE_i).

$$BCanalElev\_b = \frac{CE_b - RE_i}{RE_i} \qquad (I.3)$$

Irrigated Area (IrrgArea_)

This explanatory variable captures the amount of irrigated area in the area-buffer in squared kilometers. These values are calculated using the Colorado Division of Water Resources potential irrigated fields map and GIS Spatial Analyst tools.

Canal Seepage Indicator (AveVolSeep_)

An explanatory variable is computed to provide an estimate of the amount seeped in the area-buffers to the groundwater. The seepage volume calculation is reliant on a user defined coefficient ($\bar{s}_c$) that specifies, for canal c, the fraction of the total diversion (D_c) that will flow to the groundwater along the run of the canal (from the head gate to the end of the canal). The total seepage (S_c), in canal *c*, is computed using the diversion flow (D_c) and the canal seepage coefficient.

$$S_c = D_c \cdot \bar{s}_c \quad (I.4)$$

The estimated seeped amount in the area-buffer is calculated as a fraction of the total seepage of the canal. The area-buffer seepage ($S_{c,b}$), for canal *c*, is computed as the total seepage per unit length times the length of the canal intersecting the area-buffer.

$$S_{c,b} = D_c \cdot \bar{s}_c \frac{L_{c,b}}{L_c} \quad (I.5)$$

where, L_c = the total length of canal *c* and $L_{c,b}$ = the length of the canal *c* that lays in area-buffer *b*. The length of each canal per area-buffer is calculated during the data preparation summing the canal line lengths in the area-buffer and storing the results grouped by the corresponding canal *HydroID* and the *bufferID.*

The explanatory variable (*AveVolSeep_*) for each area-buffer, it is calculated as the average seeped volume of the canals in the buffer. The average seeped volume (S_b) in the buffer *b* is calculated as:

$$S_b = \frac{\sum_{i}^{C_b} S_{i,b}}{C_b} \quad (I.6)$$

where, C_b = number of canals present in the area-buffer *b, $S_{i,b}$* = the seepage of the canal command area *i* in the buffer *b*.

This indicator is factored by the percent reduction when simulating management alternatives in *River GeoDSS*. The seepage reduction fraction for canal c (R_{Sc}) is incorporated in the explanatory variable as follow:

$$S_b = \frac{\sum_{C_b} \left[\frac{D_c \cdot \bar{s}_c \cdot L_{c,b}}{L_c} \cdot \left(1 - R_{Sc}\right) \right]}{C_b} \quad (I.7)$$

Canal Seepage Reduction (PercSeep_)

An indicator for the canal seepage reduction fraction in the area-buffer is incorporated into the explanatory variables. The seepage reduction fraction corresponds to the fraction of the baseline seepage that was reduced by improvements in the canal conveyance efficiency. The area-buffer indicator is computed as the average of the fractions for the set of canals intersecting the area-buffer (C_b). The indicator for area-buffer b can be calculated as:

$$PercSeep\_b = \frac{\sum_{i=1}^{C_b} R_{S_i}}{C_b} \quad (I.8)$$

where, R_{S_i} = Seepage reduction fraction for canal i.

Aquifer Recharge (Rech_)

An explanatory variable is introduced to provide the ANN with information about the amount of water that is deep-percolated to the groundwater from irrigation practices. The aquifer recharge is approximated as a fraction of the water available to the fields. Water available for irrigation (F_c) for canal command area c, is approximated as the diverted water minus the seepage losses. Assuming an average leaching fraction (lf), the aquifer recharge volume (R_c) from canal c is calculated as:

$$R_c = F_c(lf) = (D_c - D_c \cdot \bar{s}_c)lf \quad (I.9)$$

where, D_c = the diversion of canal c, $\bar{s}_c$ = the average seepage coefficient for canal c.

The recharge indicator for area-buffer b is calculated using the proportional aquifer recharge amount for all canals that irrigate the buffer. The average recharge for area-buffer b ($\bar{R}_b$) is calculated as:

$$\bar{R}_b = \frac{\sum_{i=1}^{C_b} \frac{lf(D_i - D_i \cdot \bar{s}_i)A_{i,b}}{A_i}}{C_b} \quad (I.10)$$

where, D_i = the canal i diversion in acre-ft/week, C_b = the number of canals that irrigate fields in area-buffer b and $A_{i,b}$ = the area irrigated by canal i in buffer b. A_c = the total area irrigated by canal i.

During the management scenarios simulation, the aquifer recharge reduction is implemented using the recharge reduction factor (R_R). The recharge indicator is calculated as:

$$\bar{R}_b = \frac{\sum_{i=1}^{C_b} \frac{lf(D_i - D_i \cdot \bar{s}_i)A_{i,b}}{A_i}(1 - R_R)}{C_b} \quad (I.11)$$

Notice that the recharge indicator becomes Equation I.10 when the recharge reduction factor R_R equals to zero (e.g., baseline and management alternatives that don't include recharge reduction).

Recharge reduction is achieved by improvement of application efficiency at the field operations, resulting in a new leaching fraction (lf'). The recharge indicator can be expressed as a function of the scenario current diversion and improved leaching fraction as:

$$\overline{R}_b = \frac{\sum_{i=1}^{C_b} \frac{lf'(D_i' - D_i' \cdot \overline{s}_i')A_{i,b}}{A_i}}{C_b} \quad (I.12)$$

Where D_i'= Diversion in the simulated recharge reduction scenario for canal i, and $\overline{s}_i'$= average adjusted canal seepage coefficient to produce the management scenario seepage. The adjusted leaching fraction can be calculated assuming that the scenario aquifer recharge (R') equals the reduced baseline recharge ($R(1-R_R)$).

$$F' \cdot lf' = F \cdot lf(1-R_R) \quad (I.13)$$

$$lf' = \frac{F}{F'} lf \cdot (1-R_R) = \frac{F}{F - F \cdot lf \cdot R_R} lf \cdot (1-R_R) = \frac{lf \cdot (1-R_R)}{(1-lf \cdot R_R)} \quad (I.14)$$

Aquifer Recharge Indicator (PercRech_)

An indicator for the recharge reduction factor in the area-buffer is used as explanatory variable. The indicator is the average of the individual recharge reduction fraction (R_R) overall canals that irrigate fields in the area-buffer.

$$PercRech\_b = \frac{\sum_{i=1}^{C_b} R_{R_i}}{C_b} \quad (I.15)$$

Where R_{R_i}= Recharge reduction fraction for canal i. C_b = the number of canals that irrigate area-buffer b.

Groundwater Pumping (AvePumped_ and NoPumps_)

Historical pumping data in the area-buffers is used as explanatory variable for the ANN stream-aquifer interaction modeling. Two explanatory variables are created to indicate the magnitude and density of the pumping in the area-buffers. The first one (*AvePumped_b*) is the total volume pumped from the aquifer and the second one (*NoPumps_*b) is the number of active pumps in the area-buffer *b*.

The pumped volume is increased in by the factor indicated by the simulated management scenario. The vertical drainage alternative pumped water (P') is calculated as:

$$P' = P \cdot (1 + I_p) \tag{I.16}$$

where, P = historical pumped water, and I_p = the factor in which the pumping is increased.

The additional pumping (ΔP) can be calculated from the historical records of the pumps located in the grouping areas using the I_p factor or it can be extracted from the total scenario pumping (in MODFLOW output) using the following relationship:

$$P' = P + \Delta P = P(1 + I_p) \tag{I.17}$$

where P' = management scenario pumping and P = baseline pumping. Rearranging the equation terms ΔP is computed as:

$$(P' - \Delta P)(1 + I_p) = P' \tag{I.18}$$

$$\Delta P = P' \frac{I_P}{1 + I_P} = P'\left(1 - \frac{1}{1 + I_P}\right) \tag{I.19}$$

MODFLOW-MT3DMS VARIABLES FOR ANN TRAINING

The following variables are processed and included in the ANN training dataset, for the baseline and management alternatives, using Geo-MODFLOW with the user specified binary MODFLOW-MT3DMS output files. The Geo-MODFLOW queries the individual cell outputs. The geo-processed MODFLOW-MT3DMS grid cells are clipped to the grouping areas. All cells outputs are adjusted proportional to the area inside the grouping area. A proportionality factor, defined as the ratio between the cell area inside the grouping area and total area of the cell, is multiplied times the cell output to compute the corresponding grouping area portion.

MODFLOW-MT3DMS River Cells Grouped Variables

The following output variables of the training datasets are populated for both the Arkansas River (Main River) and the tributaries using the cells the MODFLOW-MT3DMS flagged river cells. These variables summarized per grouping area.

Main River Aquifer Return (OUTPUTInRiverArk)

This variable includes the total water volume that flows from the aquifer to the river during each time step in the grouping area.

Tributary Aquifer Return (OUTPUTInRiverTrib)

This variable equals the total water volume that flows from the aquifer to the tributary streams during a time step in the grouping area.

Main Stream depletion (OUTPUTOutRiverArk)

This variable contains the sum of the water depleted from the main river into the aquifer during a time step in the grouping area.

Tributary depletion (OUTPUTOutRiverTrib)

This variable contains the sum of the water depleted from the tributaries into the aquifer during a time step in the grouping area

Main Stream/Aquifer Salt Load (OUTPUTQualityArk/OUTPUTQualityTrib)

These variables summarized the total salt load to the main river and tributaries from the aquifer in the grouping area.

Main Stream/Aquifer Salt Load (OUTPUTConcArk/OUTPUTConcTrib)

These variables contained the computed concentration of water returned to the main river and tributaries respectively. It is calculated as the ratio between mass returned and volume returned.

All MODFLOW-MT3DMS Cells Grouped Variables

Using all the cells in the grouping area, the following variables are computed for the ANN training dataset:

Aquifer Recharge (AquifRech)

This variable contains the sum of the total aquifer recharge amount for all the cells and all the MODFLOW-MT3DMS layers in the area-buffers. An output variable is created per area-buffer in the grouping area.

Simulated Drainage Volume (DrainReturn)

This variable summarizes the total drained water volume in the grouping area.

Simulated Drained Salt Load (DrainSaltLoad)

This variable contains the salt load contributed by the drained water that flows to the surface system.

MODFLOW-MT3DMS Pumped Water (OUTPUTPumped)

This variable summarized the MODFLOW-MT3DMS groundwater pumped in a time step from the grouping area.

Pumped Salt Load (OUTPUTPumpedSalt)

This variable contains the total salt load from the pumping activity in MODFLOW-MT3DMS.

Canal Seepage (CanalSeepage_)

For each area-buffer in the grouping areas the total seepage is summarized to the training dataset.

ANN TRAINING DATABASE

The tool produces a database containing the ANN training dataset. The database includes three tables:

General Information Table (ANN_InputOutput_Original_GeneralInf)

This table contains general information about the source tables, preferences, variables generated description and date of execution.

Data Sources Information Table (ANN_InputOutput_Original_DataSources)

This table holds information about the scenarios used to generate the dataset. It contains the scenarios number and names keys (unique identifiers) as well as the MODFLOW file name used to generate the cases for each management alternative.

Data Sources Information Table (ANN_InputOutput_Original)

This table contains the sets of inputs/output for ANN training and simulation. The training cases will have sets of inputs and corresponding outputs. The simulation cases correspond to pre-calculated explanatory variables that will be available basin-wide at simulation time. The input/output cases (table rows) have information about the grouping area, the scenario where it came from as well as the time step for which it was generated.

ANN Training Dataset Files Description

The *ANN Database Management* utility exports the dataset to a set of comma separated files (*.CSV) files for training, testing and simulation. The files are created in the folder specified in the *Output Folder* box using the prefix name given by the user in the *File Base Name* (Figure 4.12). The files created are:

ANN_to_MODSIM_DataSources.csv contains the list of scenario number id and name.

ANN_To_MODSIM_CONST.csv holds a table with values for the explanatory variables that are constant for all the modeled time steps. It is structured with the explanatory variables in the columns and the grouping areas in the rows.

ANN_To_MODSIM_AvgOutputs.csv provides the average values for the output variables to be predicted.

ANN_To_MODSIM_AvgInputs.csv contains a summary table with average values for recurrent explanatory variables.

ANN_OutputVarLabels.csv provides the labels and units information for the output variables. These values are user-defined in the *ANN Database Management* utility support tables.

ANN_To_MODSIM.csv contains the generated dataset including all the explanatory variables (and available recurrent variables) for all the scenarios. This table is used for *River GeoDSS* testing purposes.

ANNTrain_X.csv contains the training dataset for each group *X* defined in Figure 4.11.

ANNTest_X.csv contains the testing dataset for each group *X* defined in Figure 4.11. It includes all available time steps (some of the initial time steps are excluded from training for not having recurrent variables) and it might not include the training dataset filters, if selected by the user in the interface. This dataset might also include training cases since it will provide an overall performance measurement.

ANNIOInfo.csv contains information for MATLAB ANN training. This file includes the number of previous time steps included in the dataset, the number of area-buffers, the training and testing grouping areas, the name of explanatory variables, name of recurrent variables and output variables.

APPENDIX II

Electronic only (CD Attached)

ANN Stream-Aquifer Interaction Modeling Performance Evaluation

APPENDIX III

RIVER GEODSS USER SUPPORT

This section provides detailed information of the *River GeoDSS* components and procedures to provide the user with in-deep exposure to details in the *River GeoDSS* implementation and usage.

GEO-MODSIM DATA-MODEL DESCRIPTION

This section describes in detail the Geo-MODSIM data-model components and fields. A Geo-Referenced data-model (see Figure 3.4) was designed and implemented to support the integration of MODSIM and the GIS geometric network. A feature dataset called "*MODSIM_Network*" holds the elements of the geometric network. The geometric network is implemented with Simple Edges - Simple edges are always connected to exactly two junctions, one at each end. Point and line type feature classes hold the elements of the network grouped by the MODSIM object types. The data-model geometric network is created combining these feature classes bringing together all the system elements available in the geo-database. The data-model adopts the ArcHydro (Maidment 2002) *HydroID* concept, which identifies each element in the network with a unique number. All the feature classes' *HydroID* fields are populated with this unique identifier using the ArcHydro tools. This section is focused on the basic fields and the custom field created for the *LAR GeoDSS*. As a rule of thumb, fields prefixed *MOD_* are processed to generate the model input variables. There are common fields for all the feature classes. The following fields are available in all the feature classes:

- *HydroID*: unique identifier for all the objects in the network.
- *MOD_Output*: field used by *River GeoDSS* for spatial output display. This field is populated automatically during the spatial output display feature form the MODSIM output database. It can be used for analysis on a time step basis using the Spatial Output Display tool to populate it for the time step of interest.
- *MOD_Name*: contains the unique name for the MODSIM object. This name can be assigned before creating the network if there are objects that have a pre-defined name; otherwise, it will be automatically assigned during the MODSIM network generation. **It is highly recommended that once the MODSIM network is created the user do not edit this field because can corrupt the *River GeoDSS* project**.
- *MOD_Cost*: this field holds link costs in the data-model. These values can be transferred to the MODSIM objects using the Geo-MODSIM interface menu items (*Tools→Load DataModel Data*).
- *MOD_Number*: This field is populated during the MODSIM network creation in Geo-MODSIM. **This field should not be edited by the user at any time**.

Geometric Network Edges

Two feature classes constitute the geometric network Edges: (1) the Modsim_Canals feature class and (2) the Modsim_Streams feature class. Common fields for the edges feature classes are:

- *FlowDir*: text field indicating the link direction of the flow. This field allows batch-resetting of flow directions in the network using the ArcHydro tools. This field can be populated manually or using the flow direction tools in ArcHydro.
- *Edge Type*: this field is populated with a text to flag artificially created links with the word "*shoreline*". Null values indicate default canal links and "*Flowline*" indicates streams imported from NHD dataset.
- *ANNReturn*: [True/False] field defined for the line type object, indicating if return flow will be calculated at the *to-node* of the link. This is field is commonly empty for canal links.

Modsim_Canals Feature Class

The *River GeoDSS* fields specific for this feature class are:

- *MOD_USG*: [0/1] binary field indicating if the node is active in MODSIM.

DemandID: links populated with this value indicate diversion water conveyance for the entered demand node *HydroID* number.

Modsim_Streams Feature Class

ARK_ReturnType: this field is customized for the Arkansas River modeling. It represents the type of return flow to be calculated on the links flagged to have return flow. The return flow is modeled at the *to-node* of the link. The "*Main_River*" flag triggers the use of the ANN trained for the Arkansas River, the "*Tributary*" flag triggers the usage of the ANN trained for the Arkansas Valley tributaries.

Geometric Network Nodes

Six feature classes are used to represent the geometric network nodes: Modsim_Demands, Modsim_Gauges, Modsim_NonStorage, Modsim_ReservoirNodes, Modsim_Sinks and the automatically created MODSIM_Network_Net_Junctions. The MODSIM_Network_Net_Junctions are usually default nodes in the network (where no other node was defined). The other network nodes usually are manually edited by the user. Common fields to the node feature classes are:

- *BufferID*: text field representing the grouping area (G) and the area-buffer number (*B*) where the node falls in. The format is "*G_B*". Null values are allowed for nodes outside of the area-buffers.
- *MOD_Cost*: holds the node priorities for the MODSIM nodes in the data-model. This value is imported to the MODSIM objects using the Geo-MODSIM tools (*Tools→Load DataModel Data*).

The Modsim_Sinks feature class doesn't have additional fields. Specific fields for each of the other MODSIM node feature classes are described next.

Modsim_Demands Feature Class

- *WD*: is the number corresponding to water district assigned to diversion structure by the Colorado Division of Water Resources (CDWR).
- *CODE*: diversion structure identifier assigned by the Colorado Division of Water Resources.

- *TotIrrgArea*: user calculated irrigated area. This value can be populated from the irrigated fields map using the "*Names_*" field to relate the parcels polygons. Its value is in squared meters.
- *TotCanalLength*: user calculated length of the canal downstream of the diversion structure. This value is stored in meters.
- *MOD_SeepCoeff*: contains the assumed baseline average channel loss coefficient ($\bar{s}$) that multiplied times the diversion will approximate the total volume seeped along the length of the canal.
- *MOD_RechRed*: contains the active recharge reduction factor. This field is populated at run time by the management scenario manager with the active scenario values.
- *MOD_AdjSeep*: holds the processed canal seepage coefficient adjusted to the active scenario such that multiplied time the scenario flow results in the targeted baseline seepage reduction.
- *MOD_AddPumping*: Additional pumped value for the active time step and scenario. This field is updated at run time for the active time step.
- *MOD_DiverRed*: holds the calculated diversion reduction for the active time step.
- *MOD_BaseOutput*: Baseline run diversion for the active time step. This field is populated at run time for the active time step.
- *MOD_BaseSeepOut*: baseline run total seepage calculated for the diversion along the conveyance length.

Modsim_Gauges Feature Class

- *HydroCode*: identifier assigned to the station. The field is type text and contains the USGS sequence of numbers that identify the station or the CDWR structure name (letters).
- *GaugeID*: station identifier for the time series database. This value corresponds to the node's *HydroID*. The *GaugeID* field needs to be updated to represent only the stations that contain data. It can be populated copying the HydroIDs for nodes where *Calib_Active="YES"*.
- *Calib_Active*: [Yes/No] field indicating if the node is active during calibration; therefore, a calibration structure will be created around the node.
- *UPS_Source*: [Yes/No] field indicating if the node will be use as a source of the system (the most upstream stations will be flagged with "YES").
- *Ark_CalibRelevance*: relative value used in Geo-MODSIM calibration to set cost on the calibration links, giving priority to provided calibration flows to the nodes assigned with higher relevance.

Modsim_ReservoirNodes Feature Class

- *Capacity_AF*: capacity of the reservoir in acre-ft. This value is imported to the corresponding MODSIM nodes using the Geo-MODSIM data import tools.
- *WD*: is the number corresponding to the water district assigned to a diversion structure by the Colorado Division of Water Resources (CDWR).
- *CODE*: diversion structure identifier assigned by the Colorado Division of Water Resources.

- *MODSIM_Status*: [Active/Inactive] flag that triggers the setting of the targets to enable/disable the storage of water in a reservoir. The *River GeoDSS* populates the reservoir targets time series with zero when the reservoir is *Inactive*.

Modsim_NonStorage Feature Class

- *ARK_Type*: indicates the type of node for network adjustments. This node can be a "*regular node*" in which case the resulting node will be a non-storage node. The "*Terminal Interface*" and "*Reservoir Interface*" nodes will be transformed to a flow-through demand node with the value in the field "*ARK_ReturnFraciton*" specified as the operational flow that flows downstream. Reservoir Interfaces are located at the end of canals where they flow into a reservoir. These nodes allow storing in the reservoir a fraction of the water in the canal.
- *ARK_ReturnFraction*: fraction returned to the system as a result of operational flows at the end of the canals.

GEO-MODSIM SYNCHRONIZATION TABLES

A set of tables are used to synchronize the GIS geometric network and the MODSIM Network. This section describes these table features. Three tables are used to synchronize and support operations that involve linkage between MODSIM and GIS objects.

The first table is named *MODSIMInfo*, it contains information regarding the active network file path, the active scenario, the status of the dialog [open/closed] and a list of network for which alternate points of diversion has been adjusted. The user is discouraged to alter/edit this table at any time; doing so, could end up in malfunctioning of the *River GeoDSS*.

The second table contains relational information between nodes in the MODSIM network and the geometric network. This table is named *MODSIM_SYNC_Network_NODE*. The table fields are:

- *NodeNo*: MODSIM node number.
- *NodeName*: MODSIM node name
- *ClassID*: internal identifier of the feature classes the ArcMap project. This number is assumed does not change during the live of the project; however, layer manipulation in ArcMap might result in changes of this identifier.
- *OID*: internal number that identifies the object in a feature class.
- *NodeType*: MODSIM node type. It can be *Demand*, *Non-Storage*, *Reservoir* or *Sink*.
- *X*: x axis coordinate (longitude) from the geo-referenced object. This value is used to resolve inconsistencies in the sync process.
- Y: y axis coordinate (latitude) from the geo-referenced object. This value is used to resolve inconsistencies in the sync process.
- *WD*: is the number corresponding to water district of a diversion structure assigned by the Colorado Division of Water Resources (CDWR). Used for demand nodes with diversion records.
- *StructureID*: diversion structure identifier assigned by the Colorado Division of Water Resources. Used for demand nodes with diversion records.

- *GaugeID*: HydroID value for demand nodes that play the role of gauging stations, all other nodes will have a null value.
- *Calib_Structure*: text combining the *Calib_Active*: and *UPS_Source* flags for gauging stations.
- *BufferID*: text field representing the grouping area (*G*) and the area-buffer number (*B*) where the node falls in. The format is "*G_B*". Null values are allowed for nodes outside of the area-buffers.
- *HydroID*: shallow copy of the node object's *HydroID*.

The following fields are used to create multi-links and bypass links in the MODSIM network.

Orig_DSNode: Name of the original (geometric network) downstream node. It is populated, during the creation of the MODSIM network, only when a single node is located upstream.

Orig_UPNode: Name of the original (geometric network) upstream node. It is populated, during the creation of the MODSIM network, only when a single node is found downstream.

The third table contains relational information between links in the MODSIM network and the geometric network. This table is named *MODSIM_SYNC_Network_LINK*. The table fields are:

- *LinkNo*: MODSIM link number.

- *Name*: MODSIM link name.
- *ClassID*: internal identifier of the feature class in the ArcMap project.
- *OID*: internal number that identifies the object in a feature class.
- *FromNode*: name of the MODSIM node upstream of the link.
- *ToNode*: name of the MODSIM node downstream of the link.
- *NetEID*: geometric network unique identifier for the link.
- *ANNReturn*: copy of the ANNReturn flag in the base feature class.
- *ARK_ReturnType*: copy of the *ARK_ReturnType* flag in the base feature class.

GEOMETRIC NETWORK PROCESSING

Imported networks usually need processing to move water correctly and become functional in GIS. A functional geometric network is required to generate the MODSIM network. Few tips are described herein.

Flow Directions

ArcHydro tools provide the initial assignment of flows using the digitized direction. The NHD network is usually accurate on the flow directions according to the digitized direction for stream. In canal lines, fine tuning of the direction is usually needed. An ESRI support page downloaded tool is useful to assign individual links flow direction based on the digitized direction. Alternatively, the field *FlowDir* in the data-model combined with the assign ArcHydro flow direction tool (from field) can be used to change individual links flow direction. The edited direction can be saved to the geodatabase using the ArcHydro tool. Flow direction is reset every time a new network is generated. The edited flow directions can be loaded later on using the data-model saved values.

Simple Edges and Water Movement

All points in the network should be connected to successfully build the MODSIM network. The nodes connection to the network process can be done using the "connect" tool. It is advised to store the flow direction using ArcHydro tools in advance to facilitate restoring the flow direction after the nodes are connected to the network.

MODSIM Network Execution Pre-processing

The standard Geo-MODSIM run performs transformations to the Base-Network to accommodate the *River GeoDSS* features. The following operations are carried out before the network is solved:

It creates a copy of the MODSIM Base-Network using the Base-Network name and the simulation scenario name. If the WQM is active, it stores the water quality data to the *River GeoDSS* project Water Quality Database, using the same MODSIM basename and "*TS.mdb*". Finally, the current preferences (active network and *River GeoDSS* interface status) are stored in the data-model database.

If the WQM is active, the module initializes the water quality variables in the nodes and links *TAG* objects.

Network flow is blocked downstream of the Geo-MODSIM demand nodes (gauging stations are not included in this group).

Adjust the system interfaces, converting them to *flow-through* nodes and assigning the corresponding data-model return flow fraction. The interfaces priorities are set sequentially, starting at 4800 and subtracting a unit for each subsequent interface.

It creates the *flow-through* demand structure at the Geo-MODSIM demand nodes, allowing diverted water to flow to the terminal interfaces. The demand node downstream link is closed to flow.

A system sink is attached to the most downstream end of the network (*ARKCOOKS* station) to capture excess water created during the simulation scenarios by rejection of historical diversions. In calibration mode, the sink node is assigned with a priority of 4850; otherwise, its priority is 2000 (value related with reservoir layer priorities in simulation).

In calibration mode, the calibration structure is created. The system source node is named *CALIB_SOURCE* and the system sink in named *CALIB_SINK*. Links downstream of the gauging stations are closed for calibration. In simulation, these links are open and acts as the station bypass credit link (for output purposes). In simulation, the gauging stations are set to an incremental priority starting at 5100 (to remove the gauging station from the water rights allocation system). The link from the source to the station's downstream node is created and named with the station name suffixed with *_CALIB_DS_SUPPLY*. The *Ark_Calib_Relevance* data-model field value (*Rel*) is used to assign the link cost using the formula: $\cos t = -5 + \mathrm{Re}\, l$. The system inflow links created for the most upstream gauging stations are called after the station name suffixed with *_CALIB_SOURCE*. The cost on the system inflow links is -7. The *_CALIB_SOURCE* link creation is triggered by the data-model field *UPS_Source* set to "YES". The excess flow link, from the station to the system sink node, is created and named with the station name and the suffix *_CALIB_SINK*.

1. In simulation mode, the calibration network results are used to set to the maximum bounds on the calibration links (suffixed with *_CALIB_DS_SUPPLY*, *_CALIB_SOURCE* and *_CALIB_SINK*). For each gauging station node, the cost of the calibration links is set to -51000 minus a node counter.

2. Diversions are updated for management alternatives simulation. The demands are reduced according with the amounts specified for canal seepage reduction, aquifer recharge reduction and vertical drainage pumping.

3. Create the Sub-Network and save the *River GeoDSS* project, including the changes to the MODSIM network and the water quality database.

4. When using the ANN module, the module is initialized and a copy of the previous simulation scenario network results is generated. When the module is initialized, the MATLAB export files for the active trained ANN are loaded and the ANN support network structures are created.

Stream-Aquifer Interaction Grouping Areas

Grouping areas for the Neural Net-based stream-aquifer interaction modeling are a key component in the successful application of the learned relationships outside the detailed groundwater modeled area. The areas should have similar areal characteristics for the expected predictions per unit length to be in the same order of magnitude. A suggested procedure to create these areas is outlined in this section. A USGS Digital Elevation Model (DEM) is used as input for ArcHydro. The ArcHydro terrain processing steps are followed to generate catchments, drainage areas, lines and points. The grouping areas are build isolating the Main River lines from all other stream lines in the system. Points at 15-km apart are created to split the stream-aquifer interaction calculations in similar size reaches. ArcHydro Watershed Processing tool is used to define sub-watersheds for the 15-km-spaced points on the Arkansas River. Each sub-watershed is the base for the grouping polygons (adjacent areas). The grouping areas boundaries, for the most part, follow the angles of the sub-watershed delineation lines except in sub-watersheds with very narrow sections where the division lines are modified to end up with more similar-sized areas. Figure III-1 shows the grouping areas created with this procedure for the *LAR GeoDSS*. The adjacent areas of the river sections are extended on both sides of the main river to approximately the alluvial aquifer. The most far north-south irrigation canal around of the river is a good approximation to delimit the alluvial aquifer.

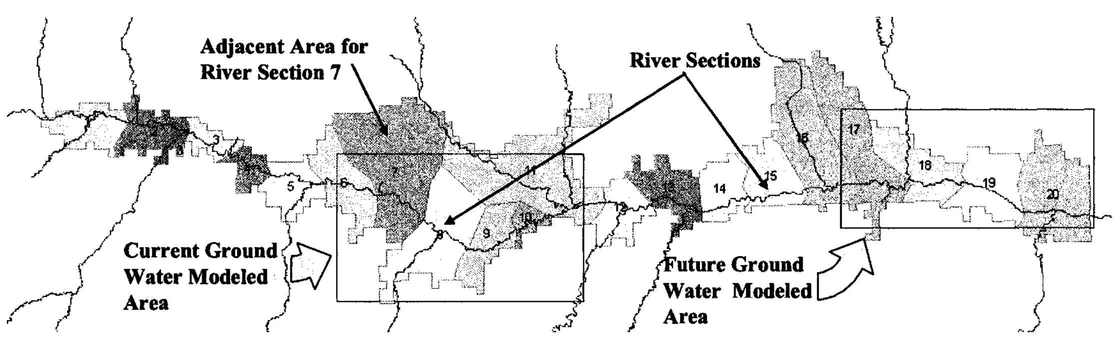

Figure III-1 – Grouping-areas for ANN stream-aquifer interaction modeling in the Lower Arkansas River

ANN Modeling Files in *LAR GeoDSS*

The MATLAB trained ANN is exported into two text files for *LAR GeoDSS* simulation. These files include all information about the training parameters that allows implementing predictions in the *LAR GeoDSS*-ANN module. The exported text files are named with the

ANN corresponding basename and the suffixes ***ANNInputs.csv*** and ***ANNWeights.csv***. The files are stored in the MATLAB workspace.

The *ANNInputs.csv* file contains the number of input variables, followed by the list of variables with the type of pre-processing function [MnMx/Std], the minimum, maximum and a sample value of the input variable in the training dataset. The file is a comma separated (csv) text file. Figure III-2 shows a sample of this file structure (as seen in Excel).

	A	B	Min	Max	Sample	F
1	ANNInputs					
2	25					
3	StreamLength	std	1.51E+01	2.28E+00	1.00E+01	
4	RiverFlow	std	4.50E+06	6.84E+06	3.61E+06	
5	BufArea_0	MnMx	3.77E+01	9.21E+01	4.38E+01	
6	AvePumped_0	std	9.58E+04	1.20E+05	9.08E+01	
7	AveDiversion_0	std	1.63E+05	1.61E+05	1.94E+05	
8	Canals_0	MnMx	0.00E+00	4.26E+04	1.93E+04	
9	AveElev_0	MnMx	-1.39E+03	-1.03E+03	-1.20E+03	
10	BCanalsElev_0	std	-1.12E+03	3.40E+02	-1.20E+03	

Figure III-2 – ANNInputs.csv file layout example

The *ANNWeights.csv* file contains information about the network, including user comments about the network and summary of the preferences used in the training. The second row includes the number of neurons in the first layer, the number of inputs, and the number of outputs. The following rows include the list of output variables and their scaling parameters, including the post processing type and the maximum and minimum values. The rest of the file includes the hidden layers' weights and biases calculated during the training. The structure of the file changes slightly depending on the type of Neural Net used for the training. Figure III-3 shows a diagram of the file structure including type-specific weights for the different types of networks. The red colored letters are labels inserted in the file to assist its reading of the different data types. The blue labels indicate the size of the block in the file. *FFBias* block is used by Feed Forward NNs, Elman and Radial Basis Networks. A sample of the file is shown in the following Figure III-4.

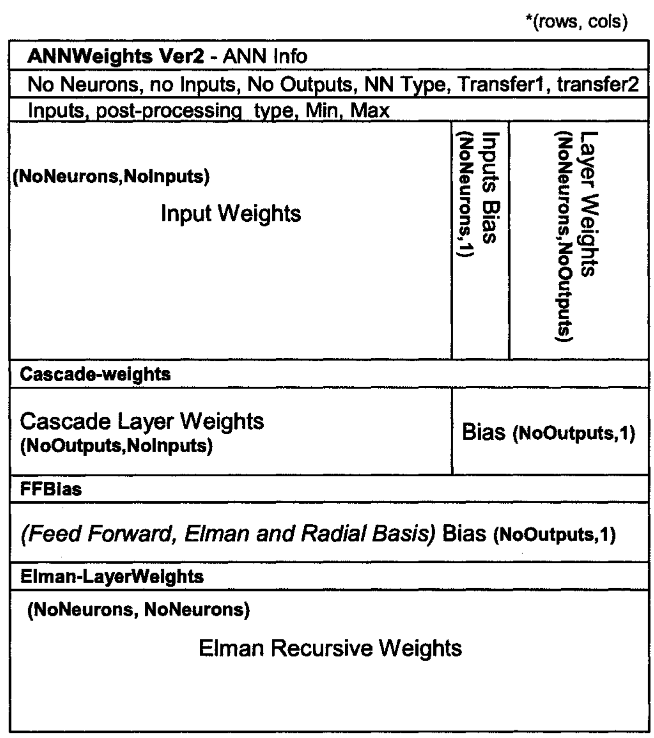

Figure III-3 – ANNWeights.csv file structure diagram

	A	B	C	D	E	F	G	H
1	ANNWeightsVer2 - File Name:AllScen_GWR_b_1ResultsSummary.mat Net No:						1	
2	405	25	2	RBNN	radbas	purelin		
3	NETRetFlov	MnMx	-1.67E+05	4.00E+04				
4	OUTPUTQu	MnMx	-3.70E+02	-8.21E+00				
5	2.98E-02	-5.35E-01	-1.00E+00	-2.67E-01	-6.07E-01	-7.23E-01	-5.69E-03	-2.63E-01
6	-4.05E-02	3.86E-01	4.70E-01	-3.68E-01	1.48E+00	8.02E-01	-2.87E-01	-4.15E-01
7	-2.24E+00	-1.93E-01	-7.76E-01	5.14E-02	2.44E-01	-9.27E-02	5.51E-02	-2.31E-01
8	-4.49E-02	-2.32E-01	4.55E-01	2.11E-01	1.82E-01	-2.38E-01	-1.89E-01	-3.61E-01
9	-4.05E-02	-1.82E-01	4.70E-01	-2.27E-01	5.46E-01	8.02E-01	-2.87E-01	-4.15E-01
10	-2.24E+00	2.57E+00	-7.76E-01	-6.82E-01	1.14E+00	-9.27E-02	5.51E-02	-2.31E-01
11	-1.97E+00	1.60E+00	-3.35E-01	1.13E+00	7.31E-02	2.56E-01	-3.93E-01	-4.72E-01
12	-1.20E-01	-6.98E-02	-3.12E-02	3.71E-01	-5.32E-01	-2.99E-01	-7.49E-02	-3.01E-01
13	-4.05E-02	8.05E-01	4.70E-01	-4.21E-01	9.85E-01	8.02E-01	-2.87E-01	-4.15E-01

Figure III-4 – ANNWeights.csv file structure example

ANN PREDICTIONS IN GEO-MODSIM

The trained Neural Net requires assembling the simulation explanatory variables sets in the same way that the training dataset were constructed. The *LAR GeoDSS* tools allow creating basin-wide spatial processed explanatory variables when creating the training dataset. The variables are carried and processed through the training process and made available for *LAR GeoDSS* simulation.

When the MODSIM model is initialized the *LAR GeoDSS* ANN module is initialized. The ANN module uses the preferences in the *LAR GeoDSS Simulation Scenario Manager* to load MATLAB trained Neural Nets from the MATLAB exported files. In addition, the basin-wide GIS-generated ANN inputs tables are loaded to the module in memory. These tables are created during the ANN training dataset generation by the *ANN Database Management Tool* based on GIS spatio-processed ANN training dataset. The ANN Module models only the links flagged with *ANN_Return* in the GIS feature class. Using this flag, the link's downstream node is marked for return flow modeling. At the beginning of each modeled time step, the ANN Module computes the ANN explanatory variables that are constant for the simulated time steps, e.g., areas, elevations, lengths, pumping, precipitation. During the MODSIM iterative process, the module computes the explanatory variables that are a function of the MODSIM-modeled variables, e.g., diversions, canal seepage, aquifer recharge. Each MODSIM iteration, the ANN module calculates stream returns/depletions per grouping area and adjusts the ANN simulation structure links flow bounds (Figure 6.10), activating the ANN predictions in the MODSIM water allocation solver. If the Water Quality Module is active, the predicted concentration is assigned to each ANN modeling support links to be part of the salt routing calculation.

The ANN-based aquifer stream interaction modeling requires assigning each node and each pumping well with the corresponding groundwater modeling grouping area ID. A preprocessor is implemented in *LAR GeoDSS* for this purpose. The tools update the *GridID* field in the *LAR GeoDSS* data-model nodes and the used-specified pumping wells feature class. Figure III-5 shows the tab in the ANN user interface () to access these ANN preprocessing tools.

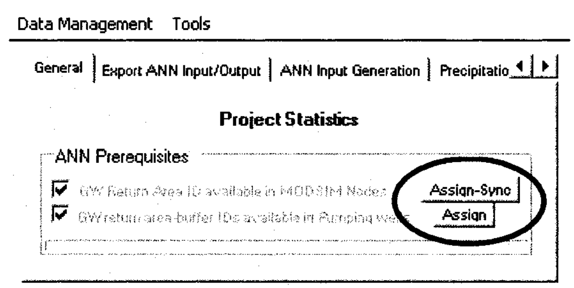

Figure III-5 – ANN preprocessing tools user interface

River GeoDSS **Water Quality Import Tool**

A tool is developed to import specific conductance data into the WQM. The tool processes data stored in the *River GeoDSS* water quality database and populates the time series object class in the module with the total dissolved solids (TDS). The *River GeoDSS* water quality database contains concentrations in microsiemens per centimeter (μS/cm). The import tool's GUI (Figure 3.14-B) provides access to a set of equations that can be used to convert the measured specific conductance (μS/cm) to TDS (mg/L). Two relationships were implemented using the equation from a regression analysis of the surface water field-collected EC and samples analyzed in the laboratory in the Arkansas Valley between 1999 and 2005 (Mueller and Gates 2006):

- ✓ Upstream of John Martin Reservoir

$$TDS\,[mg/l] = 685.87 * EC[dS/m] + 128.04 \qquad \text{(III-1)}$$

- ✓ Downstream of John Martin Reservoir

$$TDS\,[mg/l] = 728.72 * EC[dS/m]^{1.0966} \qquad \text{(III-2)}$$

Gates et al. 2006 reported similar relationship between field-measured EC and samples analyzed in the laboratory using the surface water sampling in the LARV. These surface water relationships are:

- ✓ Upstream of John Martin Reservoir

$$TDS\,[mg/l] = 859.7 * EC\,[dS/m]^{\,0.88} \qquad \text{(III-3)}$$

- ✓ Downstream of John Martin Reservoir

$$TDS\,[mg/l] = 727.7 * EC\,[dS/m]^{\,1.1} \qquad \text{(III-4)}$$

Figure III-6 shows a comparison of the weekly average TDS (mg/L) calculated with the different equations, using the USGS measured EC (μS/cm) at Coolidge, KS, gauging station (ARKCOOKS). Using the upstream equation to represent the downstream TDS will introduce a small error. For equations III-1 and III-2, it was found to under predict the TDS up to 14% and for low concentrations over predicts up to 20%. For equations III-3 and III-4, the upstream equation under predicts the downstream TDS up to and 15% and over predicts the lower concentrations up to 16%.

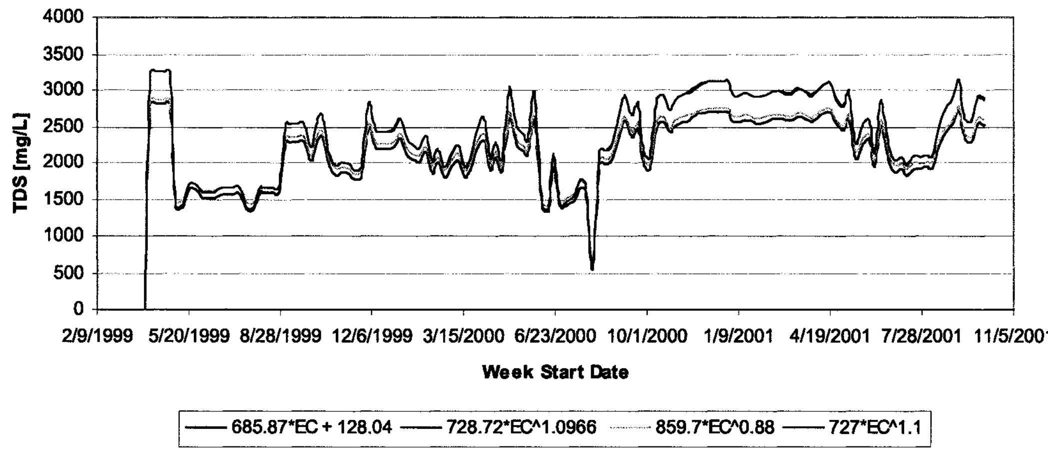

Figure III-6 – EC to TDS equations performance example

For the Arkansas River basin-wide modeling the import option that uses the average TDS of the upstream-downstream equations is utilized (Figure 3.14-B). In addition, the import tool allows using both regularly measured and sporadic (grab samples) data. A checkbox allows the user to use the available sporadic specific conductance measurements when there are no available regular records. The tool queries the main water quality database for the average of both sporadic (type = 9) and continuous (type = 2) for each MODSIM time step. The query results are analyzed and placed in the concentration time series according to the user import preferences. If available, the continuous data are used in first place. If there are less regular records than sporadic samples a weighted average is used to represent the average EC. If there is not available regular data for the time step, the average of the available sporadic samples in the time step is used. The time series object requires to have the first modeled time step date in the first row of the time series table, therefore when no data is available a 0 mg/L will be assigned. When sporadic measurements are used, the missing periods are skipped from the time series allowing the MODSIM time series logic to fill missing values with the previous available concentration value until a new concentration value is found. On the other hand, when sporadic values are not used the missing values will be assumed as 0 mg/L.

GEO-MODFLOW SUMMARY CALCULATION DETAILS

Geo-MODFLOW relies on the cell numbers field in the Geo-referenced MODFLOW-MT3DMS grid in ArcGIS. The cell numbers in the grid feature class correspond to the cell numbers in the first layer of the MODFLOW-MT3DMS grid. These first layer cell numbers are used in Geo-MODFLOW to find cell numbers in other layers (MODFLOW-MT3DMS uses a different cell number for each layer). The cell number (*Cell*) of the first layer is calculated as:

$$\text{Cell} = (\text{Row} - 1) * \text{Ncols} + \text{Col} \qquad \text{(III-5)}$$

where, *Row* = the current row number from the upper left corner, *Col* = the current column number from the upper left corner and *Ncols* = the number of columns of the MODFLOW-MT3DMS grid.

The MODFLOW binary file is sequentially read, storing in memory arrays the cells values for each layer of the data under the following headings: *WELLS*, *RIVER LEAKAGE*, *ET*, *DRAINS*, *RECHARGE*, *HEAD DEP BOUNDS* and *STORAGE*. The MT3DMS concentration output file is also read to memory storing the cell-concentration for each layer using the first layer cell number as identifier. Utility functions are implemented in Geo-MODFLOW to query the Aquifer object for incoming and outgoing water using: the time step, the cell ID and the layer as an optional parameter (if no layer is specified, all layers are combined). The water constituent mass flowing out of each aquifer layer (Sink case only) is computed using the individual layer data (multiplying the volume times the concentration). The mass is totalized adding the mass for all layers. Mass sources have specified concentrations that are usually different from the aquifer concentration (MT3DMS output). Multi-layer combined concentration (*C*) in Geo-MODFLOW is computed using ***only the outgoing mass***. *C* is computed as the sum of the outgoing mass (negative sign in MODFLOW-MT3DMS output) divided by the volume of water flowing out of the aquifer.

$$C = \frac{\sum_{i=1}^{Cells}\sum_{l=1}^{NL} Vo_{i,l} * C_{i,l}}{\sum_{i=1}^{Cells}\sum_{l=1}^{NL} Vo_{i,l}} \qquad \text{(III-6)}$$

where, *Cells* = the set of cells to be queried, *NL* = the number of MODFLOW-MT3DMS grid layers, $Vo_{i,l}$ = the volume of water flowing out the aquifer at cell *i* and layer *l*, $C_{i,l}$ is the concentration for the cell *i* layer *l*. When no layer parameter is specified in the Geo-MODFLOW Select Tool summary, the summary corresponds to total water in/out the Aquifer.

Aquifer return mass to the River is computed using the aggregated value for all MODFLOW-MT3DMS layers. The value for river return flow will be zero for cells not marked as river cells; therefore, the aggregated value will correspond to river cells mass moving from the aquifer to the river. Notice that the storage term in the MODFLOW flow budget refers to the amount of aquifer storage that becomes a Source or Sink. Water entering to the aquifer storage is considered as a flow budget outflow while water released from storage is considered as a flow budget inflow. In the GMS flow budget dialog shown in the Figure 3.16, the positive storage value (source column) represents water flowing out of the aquifer storage; therefore, the net change in the cell water storage is a net reduction (lowering the water table).

APPENDIX IV

WATER QUALITY MODELING DETAILED PROCEDURES AND TOOLS

WATER QUALITY DATABASE

A database is created for each *River GeoDSS* Base-Network to store the processed water quality data and the Water Quality Module (WQM) user modeling preferences. The database is implemented in MS-Access as an efficient alternative to store object oriented MODSIM-native time series (time series object type used in the WQM). The database uses the MODSIM Network name suffixed by "*TS*" with the MS-Access files extension *(mdb)*. The database stores the network object user entered data in individual database tables. These data tables are named with the object MODSIM name. Two type of data tables are found in the database: (1) Concentration data tables and (2) flow-concentration fitted equation coefficients. Concentration data tables are suffixed with *_CONCENTRATION* and contain two columns: (1) the simulated period start date and (2) the concentration value. The fitting equation coefficients tables are suffixed with *_FITTINGCOEFS*. This single-column table contains in its rows the equation coefficients. A modeling preferences support table is stored in the database with the name *NodesWQCalibrationInfo*. This table contains water quality modeling for all the nodes in the network. *NodesWQCalibrationInfo* contains: (1) a flag (*USEQCFunction*) indicating if an equation is used to predict concentration as a function of flow, (2) the type of flow-concentration relationship equation in column *CurveType*, (3) the minimum and maximum (*Min_Bound* and *Max_Bound*) values for calibration flows concentration and (4) the data filter used for the fitting equation calculation dataset. Figure IV-1 shows an example of the internal database table structure.

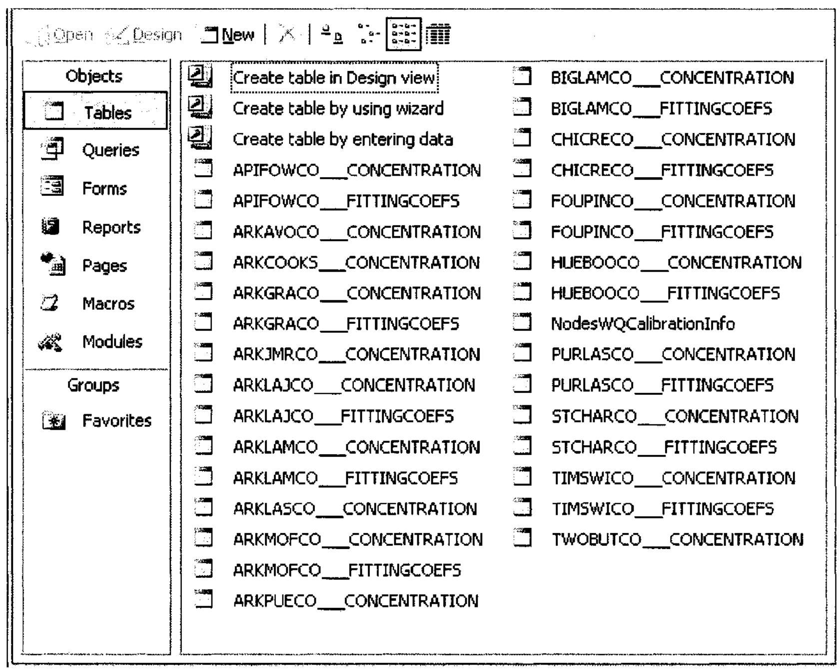

Figure IV-1 – WQM database tables sample

NETWORK TRACING ALGORITHM

The algorithm's basic loop goes through all the nodes in the network finding the terminal nodes, identified as a demand or sink node with no real links flowing out the node. For each of the terminal nodes, a nodes collection is built navigating upstream in the network through all the connected nodes towards the source nodes (identified by not having links coming into the node). The node collections supplies all nodes visited from a sink to a source node. These collections are combined into the final sequence using the following rules:

If the node to be added to the collection already exists, the node is not added.

If the node to be added is found in one of the final sequences, the member of the currently processed collection are inserted into the final sequence at the location where the node was found. The collection is then cleared and the node is not added to the collection.

The following diagrams (Figure IV-2 and Figure IV-3) illustrate the procedure implemented to trace the MODSIM network. *TODO* is a collection object that stores nodes to be processed, ← implies object code assignment, and *Final Order* is the final traced node sequence.

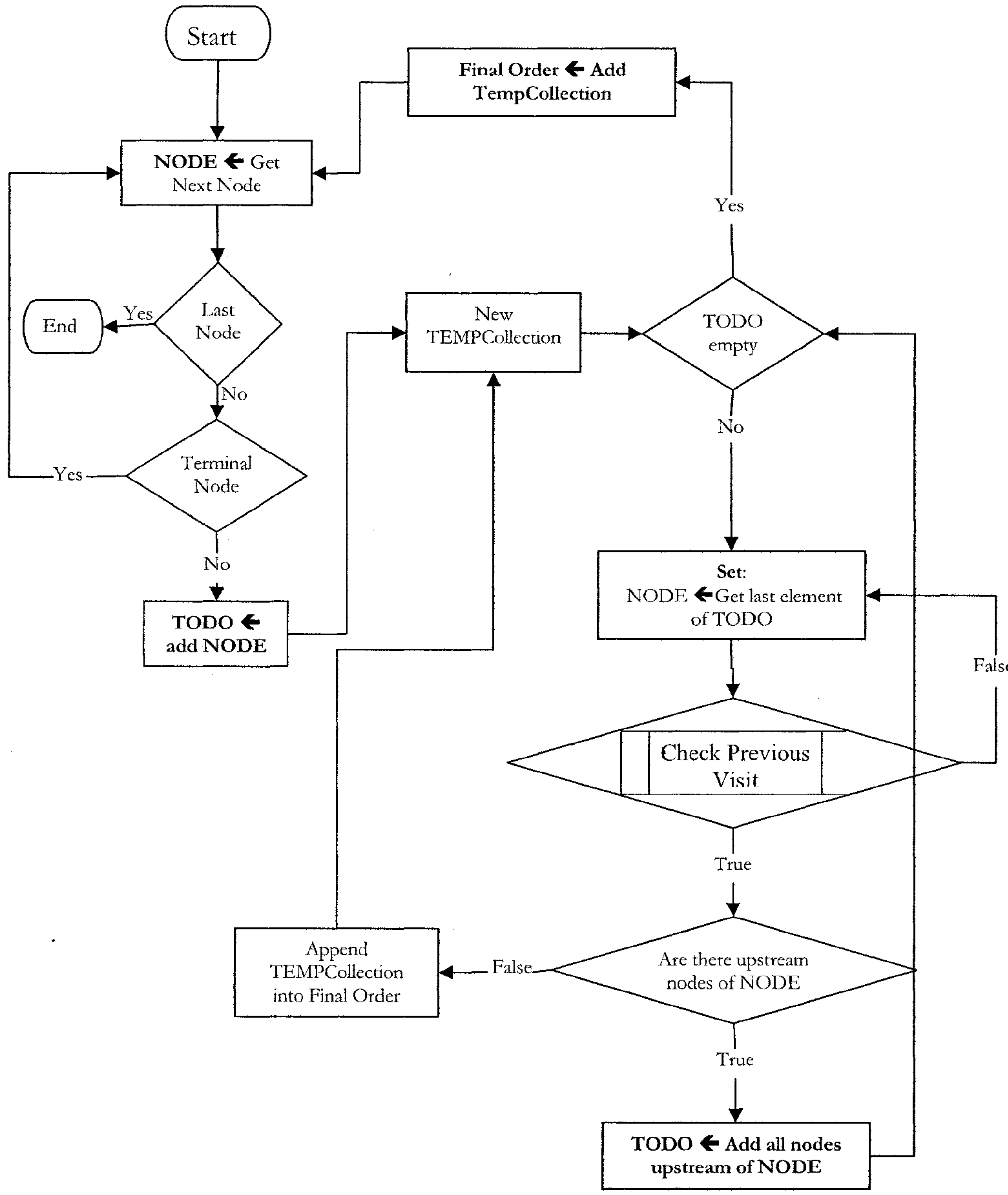

Figure IV-2 – Flowchart of the network tracing algorithm

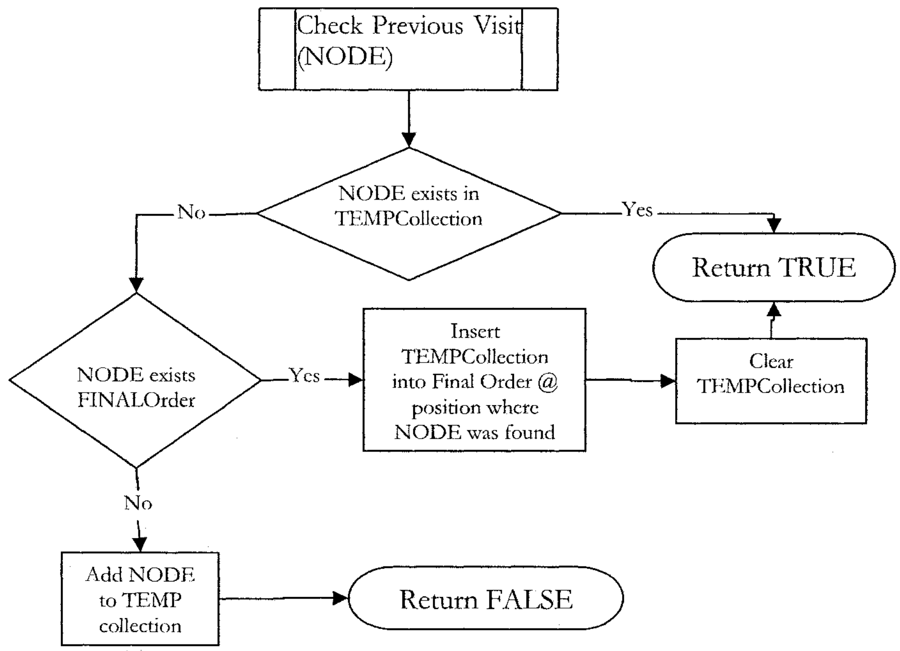

Figure IV-3 – Flowchart of the function Check Previous Visit

Conservative Constituent Routing Calculation

The algorithm developed use the principle of conservation of mass at the system nodes to calculate concentrations in all the network links. At this stage, the algorithm is applied to conservative constituents such as the total dissolved solids (salt routing).

Inflow Concentrations and Measured Control Points

The MODSIM node Tag object is used to implement a water quality class that contains: (1) a variable that implements the time series MODSIM Class and (2) a variable size array that resembles the MODSIM model time series variables populated when the model is initialized with the processed values for all the model time steps.

In the modeled basin, Total Dissolve Solids (TDS) is inferred from the measured Specific Conductance and imported to the corresponding network nodes. Water concentration is required for all system water sources for the WQM mass routing algorithm. The unknown concentrations are assigned during the calibration procedure to minimize the deviation between the calculated and measured concentration. The WQM allows the user assigning concentrations to inflows at any place in the system. The algorithm assigns *NonStorage* node-entered concentrations to the node's inflow link. In addition, demand nodes acting as source nodes (connected to a water source structure) with measured concentration will be implemented assigning concentration to the flow in the WQM support links suffixed with "_CALIB_SOURCE". Undefined values will be assigned with zero concentration and warning message will be generated (This should be avoided because it will change significantly the modeled concentration). When the measured concentration is not located at a system inflow, the measured water concentration is used as calibration check point to compare the calculated concentration with the measured one. The algorithm is designed to identify the calibration control points based on the node concentration definition and the non-existence of inflow links.

The basic routing algorithm assigns the measured concentration to local gains at gauging stations with measured concentrations. In these cases, the measured concentration is assigned to the WQM support link named with the station name and the suffix "CALIB_DS_SUPPLY".

Tributaries and River Convergence Modeling

Aquifer return flow concentration from tributaries and the main stream could be different for the links entering a convergence node. At this point, there are multiple links upstream and only one link supplying return flow; therefore, the single link concentration needs to be computed as a function of the individual concentrations. The salt load calculation at those junctions is carried out after MODSIM has converged to a solution, in which the link conveying the salt load to the convergence point is assigned with the combined return flow (tributary + Main stream). The ANN predicted salt mass load is operated with the total flow in the return link to set the concentration in the link. The resulting concentration (C) of combining tributary and main stream return flow and mass load is:

$$C = \frac{m_m + m_t}{V_T} = \frac{m_m}{V_T} + \frac{m_t}{V_T} = C'_m + C'_t \qquad \text{(IV-1)}$$

where, m_m = the mass load in the main river, m_t = the mass load in the tributary and V_T = the total combined water volume returned to the surface system. C'_m and C'_t are intermediate concentration calculations using the corresponding masses but the combined volume. During the water constituent routing calculation process, one of the intermediate concentration (C') will be initially calculated, the second intermediate concentration will be added to compute the final concentration in the link.

Water Concentration Calculation

The calculation of the constituent concentration for each link in the system is performed after the MODSIM solver has converged to a solution. The solution provides the water flow in all the links in the system. The concentration is sequentially calculated from upstream to downstream. The node calculation order assures that all the preceding concentrations are known when calculating the output concentration at any point in the system. Full mix of the constituent is assumed at each node. In consequence all the outflow nodes will have the same concentration.

The Tag object of the MODSIM links is used to carry a class that holds the concentration value for the current time step. The artificial inflow link is the only artificial one that is designed to have concentration assigned. The concentration in this link is populated each iteration based on the available user defined node-concentrations.

ANN interaction

Quantity and quality predictions of the return flow from the aquifer to the stream can be obtained in the *RIVER GEODSS* using the ANN module. The module uses a previously trained ANN to estimate the return flow water salinity. The concentration of the water added to the system from the groundwater is assigned to the links that provides linkage between the ANN source and the nodes in the system. These links are "real links", their concentration is assigned during the MODSIM solution iterative to the concentration variable in the link Tag object.

The ANN predicts total salt load to the stream, therefore the concentration is calculated as the salt mass divided by the water volume. The concentration units are converted to kg/m^3 or 1000kg/AcF in Metric and English systems respectively.

IMPLEMENTATION OF THE WATER QUALITY CALIBRATION

When the network is initialized, the algorithm identifies the network reaches upstream of all the station that have water quality data. The reaches (control volumes) are defined between water quality measuring stations and are composed of all the nodes that potentially contribute with mass to the downstream station's concentration. The algorithm trace the network upstream marking the nodes found until it reaches a demand node (that is not gauging station) or a demand node that is a gauging station and measures water quality.

During the network tracing, nodes with measured inflow, known concentration and unknown concentration are identified. The algorithm uses a table in memory to keep the relationships between each node and its corresponding downstream gauging station, as well as, the contributions from each node to the station's concentration calculation. A row is created for each node, the field *DWSStation* is used to link a node with the corresponding water quality station downstream. The table field *TypeID* is used to categorize the nodes. Initially all nodes are flagged with *TypeID* = 0. Other fields in the table are used to store mass added to and subtracted from the reach at each node. The *TypeID*=1 indicates that the node is brings a load to the reach with no concentration defined. The *TypeID*=2 indicates that is a calibration inflow to the reach. Calibration flows represent a combination of water from different sources within the reach, each one with different unknown concentrations. Initially, this calibration flow concentration is approximated with the concentration at the station upstream of the reach where calibration water is being provided but it will be adjusted later in the calibration if need it. *TypeID*=3 is used to identify nodes with measured concentration (gauging stations) or unchangeable-calculated concentration (e.g., terminal interfaces, ANN aquifer contributions). The table entries include columns to hold the flow in/out the nodes and their calculated output concentration. For each node, the algorithm calculates the total mass in and out of the reach. The mass balance terms at the nodes include: (1) reach external sources, (2) reach internal mass transports and (3) reach external sinks. Using positive (+) sign for all inputs and negative (-) sign for all the outputs, the internal mass transport will cancel out when combining all the nodes in the reach, leaving only external sinks and sources.

An iterative procedure is implemented to attempt to calibrate the model to measured concentrations. At the gauging stations, the difference between the simulated and the measured concentration is calculated. In cases where there is a discrepancy, a concentration (the same at all the unknown points) is calculated. The calculation is based on (1) the known concentration and inflows, (2) the calibration inflows using the upstream node measured/calculated concentration and (3) the inflow at the unknown concentration nodes. Equation 3.3 evaluated for the reach control volume may be written as:

$$\sum_{i=1}^{N} Q_i \cdot C_i - \sum_{j=1}^{M} Q_j \cdot C_j = 0 \qquad \text{(IV-2)}$$

where, N = the set of links with conveying mass into the reach, Q_k = the flow rate at link k of the reach, and C_k = concentration of water in link k. M = the set of links moving mass out the reach. Separating known and unknown concentration terms the mass conservation equation is:

$$Q_{out} \cdot C_{out} = \sum_{KnownC} Q_i \cdot C_i + \sum_{UnknownC} Q_i \cdot C_i - \sum_{j=1}^{M'} Q_j \cdot C_j \qquad \text{(IV-3)}$$

where, Q_{out} = the flow at the downstream end of the reach and C_{out} = the measured concentration at the downstream end of the reach. M' = the set of outflow links excluding the reach downstream station outflow link. Rearranging terms,

$$Q_{out} \cdot C_{out} - \sum_{KnownC} Q_i \cdot C_i + \sum_{j=1}^{M'} Q_j \cdot C_j = \sum_{UnknownC} Q_i \cdot C_i \qquad \text{(IV-4)}$$

Assuming a constant concentration C for all the unknown concentration inflow nodes,

$$\overline{C} = \frac{Q_{out} \cdot C_{out} - \sum_{KnownC} Q_i \cdot C_i + \sum_{j=1}^{M'} Q_j \cdot C_j}{\sum_{UnknownC} Q_i} \qquad \text{(IV-5)}$$

The value $\overline{C}$ is to be constraint between observed concentrations in the area to be valid. The range of values for each node is selected in the water quality user dialog (Figure 3.12). Initially for each reach, the nodes with *TypeID* = 1 are assigned with a concentration to match the measured concentration downstream (Equation IV-5). In the first concentration modeling, the unknown concentrations were assumed as 0, therefore the average concentration for all the unknown sources is calculated as:

$$\overline{C} = \frac{\sum_{TypeID=0(OUT)} Q_j \cdot C_j - \left(\sum_{TypeID=0(IN)} Q_i \cdot C_i - \sum_{TypeID=1} Q_i \cdot C_i \right)}{\sum_{TypeID=1} Q_i} \qquad \text{(IV-6)}$$

Notice that the measured flow and concentration at the downstream station are included in the sum of the TypeID =0 (OUT). When no nodes with TypeID = 1 are found, the concentrations in the nodes with TypeID = 2 are adjusted. These nodes were considered having known concentrations in the initial sum of mass in the reach therefore they need to be removed from the *known* sum.

$$\overline{C} = \frac{\sum_{TypeID=0(OUT)} Q_j \cdot C_j - \left(\sum_{TypeID=0(IN)} Q_i \cdot C_i - \sum_{TypeID=2} Q_i \cdot C_i \right)}{\sum_{TypeID=2} Q_i} \qquad \text{(IV-7)}$$

The outflow concentrations are a function of the current inflow concentrations. Once the inflow concentration has been adjusted, the outflow concentration change; therefore, an iterative procedure is implemented to recalculate outflow concentrations and adjust unknown concentrations accordingly until the calculated inflow concentration converges to the same concentration in consecutive iterations.

When groundwater quality modeling is active in the calibration, the ANN predicted values are net returns to the river. In these cases, the salt load to the river is treated as an input to the reach. There are few cases in which the net return is negative, indicating a removal of mass from the reach. The algorithm is implemented so that the net depletion from the river is accounted in the mass leaving the control volume (Calculated concentration at depletion point is assumed).

Convergence Criteria

The algorithm performs a set of checks to stop the iterative calculation of unknown concentrations at all the water quality stations. At any water quality station, the unknown concentrations are recomputed if (1) the difference between the calculated and measured concentration is larger than one unit, or (2) if the previous iteration calculated concentration and the current concentration doesn't change in more than 0.01 mg/L. In addition, the iteration process is limited to 60 iterations. After the 60th iteration the calibration process attempt is dropped and the latest concentrations are used to calculate concentration downstream of the control point. For each time step, the calibration process finishes with an additional iteration in which all the calculated concentrations are use to route the constituent throughout the system.

Tributary Return Flow Special Consideration

Tributaries return flow and salt load are predicted in the mayor tributaries, where continuous water flow was observed in the field. Calibration on tributaries with gauging stations need to account for the upstream contributions to set the concentration of the source link that provides the calibrated flows to match historical measured flows. The following adjustment takes place while setting the measured concentration to the station's source link. The conservation of mass at the node can be written as:

$$\sum_{IN} V_i C_i = \sum_{OUT} V_j C_j \tag{IV-8}$$

where, *IN* = the set of links entering the node and *OUT* = the set of links leaving the node. V_i = the volume of the link *i* from *IN*. C_i = the constituent concentration for link *i*. V_j = the volume of the link *j* from *OUT*. C_j = the constituent concentration in link *j*. Separating the source link terms (V_s and C_s) from *IN* and the measured terms (V_m and C_m) from *OUT* the mass balance equation at the node can be expressed as:

$$V_S C_S + \sum_{IN'} V_i C_i = V_m C_m + \sum_{OUT'} V_j C_j \tag{IV-9}$$

where, *IN'* is the set of incoming links excluding the source link. In a similar fashion, *OUT'* is the set of outgoing links excluding the stream link downstream of the station (with measured flow and concentration). The concentration in the source link will be calculated as:

$$C_S = \frac{V_m C_m + \sum_{OUT'} V_j C_j - \sum_{IN'} V_i C_i}{V_S} \tag{IV-10}$$

Additional handling is required for joints where tributary links and main river links blend together. Each of the links will have a predicted return flow and concentration. The *River GeoDSS* implements a single link to model return flows to each of the links flagged with return flows; therefore, both return flows and concentration need to be combined at the return flow link to the joining node. The flows will be added together but the resulting concentration needs to be recalculated to reflect the tributary and main stream water blend. Assuming complete mixing of the individual return flows before it reaches the node, the mass balance equation can be written as:

$$V_R C_R + V_T C_T = V_c C_c \tag{IV-11}$$

where, V_R = the volume and C_R = concentration returned to the upstream river link. V_T = the volume and C_T = concentration returned to the upstream tributary link. The combined volume and concentration are V_c and C_c. The combined volume is the sum of the incoming volumes ($V_R + V_T = V_c$). The combined concentration is computed as:

$$C_c = \frac{V_R C_R + V_T C_T}{V_c} = \frac{(V_c - V_T)C_R + V_T C_T}{V_c} \tag{IV-12}$$

Water Quality Calibration in Calibration Structures

The *flow-through* demand nodes used in the calibration structures provide water downstream with the same concentration that the water that reached the demand node. This requires special handling because the artificial connection is neglected in the network tracing algorithm. The concentration in the artificial link (*infLink*), which returns the measured water to the system as result of the *flow-through* operation, is set while calculating concentrations at the demand node. The algorithm relies on the *flow-through* demand node concentration calculation being triggered earlier than the calculation at its corresponding return node (*flow-through* Node). This is guaranteed from the network tracing calculation order. In some cases, *infLink* might contain additional flow from local inflows or other *flow-through* demands. The concentration handling at the *flow-through* node is based on calculating an equivalent concentration using the different sources and their concentrations. The procedure calculates the mass corresponding to the local inflow and loops through the *flow-through* demands associated with the non-storage node adding the mass contributions from these nodes. This procedure is performed once at a time for all the *flow-through* demands during the upstream to downstream water quality routing.

Calibration in Simulation Runs

The simulation mode with calibration results uses the water quality calibrated concentrations to set unknown concentrations in the system. In simulation, concentration is set at: (1) inflows with no measured concentrations, (2) the calibration links (suffixed with *CALIB_SOURCE* and *_CALIB_DS_SUPPLY*) and (3) reservoir inflows. The reservoir inflow link is artificial in MODSIM; therefore, it is not available in the MODSIM output file. The concentration in the reservoir node output table is used to store and later retrieve the concentration for its artificial inflow link. This calibration concentration is different than the node concentration; therefore, the output should be interpreted accordingly.

APPENDIX V

Electronic only (CD Attached)

Lower Arkansas River Basin GeoDSS User Support

APPENDIX VI

Electronic only (CD Attached)

Modeling Salinity and Waterlogging Management Alternatives in the Lower Arkansas River basin