DISSERTATION

OPTIMIZATION OF WATER INFRASTRUCTURE DESIGN AND MANAGEMENT IN MULTI-USE RIVER BASINS UNDER A CHANGING CLIMATE

Submitted by

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ABSTRACT

OPTIMIZATION OF WATER INFRASTRUCTURE DESIGN IN MULTI-USE RIVER BASINS UNDER A CHANGING CLIMATE

Traditional approaches to the hydrologic design of water infrastructure assume that the climate is stationary, and that historical data reflect future conditions. The earth's climate is not stationary but changing with time. The traditional approach may, therefore, no longer be applicable. In addition to the issue of nonstationarity of climate, the design of water infrastructure to meet a particular need, such as water supply, is often assumed to be a single-objective optimization problem and is done without consideration of other competing watershed uses and constraints such as recreation, hydropower generation, environmental flows, and flood control. Such an approach routinely fails to adequately address the challenges of complex systems such as multi-use river basins that require an understanding of the linkages between the various uses and stakeholders. Water infrastructure design will benefit from a holistic and systems engineering approach that maximizes the value to all users while serving its primary function.

The objective of this research was to identify and develop a new approach for designing and managing water infrastructure in multi-use basins that accounts for the effects of climate change by shifting the current static design paradigm to a more dynamic paradigm and accounts for other multi-use basin objectives, which may include recreation, hydropower generation, flood control, environmental flows, and water supply. This research involved an extensive literature review, exploration of concepts to solve the identified problems, data collection, and development of a decision support research tool that is formulated such that it can be used to test the viability of various hypotheses.

This dissertation presents a practical approach for designing and managing water infrastructure that uses quantifiable hydrological estimates of the future climate and accounts for multiple river basin objectives from stakeholders. The approach is a hybrid approach that applies the updated flood frequency methodology for accounting for climate change and an adaptive management framework for managing uncertainty and multiple basin objectives. The adaptive management framework defines and maintains baseline objectives of existing climate stressors and basin users while designing the primary water infrastructure, in a manner that accounts for nonstationarity and uncertainty. The adaptive management approach allows for regular review and refinement of the application of climate data and adjustments to basin objectives, thereby reducing uncertainty within the data needed for decision-making. This new approach provides a cost-effective way to use climate change projections, is applicable to all basins and projects irrespective of geographic location, size, or basin uses, and has minimal subjective components thereby making it reproducible.

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CHAPTER 1: INTRODUCTION

1.1. Problem Statement

Traditional hydrologic design of water infrastructure assumes that the climate is stationary (Brown, 2010, Galloway, G.E., 2011, Milly et al., 2008), and hence, historic data reflect future conditions. The earth's climate is not stationary but is changing with time (IPCC, 2014). The Intergovernmental Panel on Climate Change (IPCC) defines climate as the statistical description in terms of the mean and variability of surface variables such as temperature, precipitation, and wind over a period ranging from months to thousands or millions of years (IPCC, 2001). Climate Change is expected to result in an increase in the severity of extreme hydrologic events in many parts of the world (Christensen & Busuioc, 2007). Rising temperatures are also likely to result in more intense storm surges, which would require bigger flood control structures for mitigation. Floods may lead to loss of lives, property and stormwater pollution, and sanitation issues which may have adverse effects on public health. A shift from the traditional approach, which assumes that the climate is stationary, to a dynamic approach that accounts for the changing climate, is therefore urgently needed (Brown, 2010, Trinh et al., 2016).

The design of water infrastructure to meet a particular need is often considered a single-objective optimization problem and done without considering other basin constraints and competing watershed uses which may include recreation, hydropower generation, flood control, environmental flows, and water supply. The single-objective design approach often fails to adequately manage the challenges of complex systems such as multi-use river basins that require an understanding of the linkages between the various uses and stakeholders

(Anderson et al., 2008).

The design of water infrastructure will benefit from a holistic approach that serves its primary function, which may be either flood control, water supply, power generation, or recreation, under a changing climate and, at the same time, ensures that there are no negative impacts to other basin objectives or constraints.

This dissertation provides a hybrid and systems approach for designing and managing water infrastructure that uses quantifiable hydrological estimates of the future climate to address the issue of climate nonstationarity and accounts for multiple objectives from multiple basin stakeholders.

This dissertation is made up of eight chapters. Chapter 1 describes the problem statement and research approach. Chapter 2 identifies the research questions and tasks that need to be performed to develop the new nonstationary and multi-objective approach. Chapter 3 evaluates existing nonstationarity methods and recommends a hybrid framework for accounting for climate change in the design and management of water infrastructure. Chapter 4 describes the adaptive management element of the hybrid framework to address uncertainty and account for multiple basin objectives. Chapter 5 describes the development of hydrologic and hydraulic data and numeric models needed to transform climate data into design parameters such as flow and water surface elevations. Chapter 6 details the new approach, based on the results from Chapters 4 and 5, for designing and managing water infrastructure that accounts for nonstationarity due to climate change and multiple objectives from multiple stakeholders and demonstrates how the new approach can be applied in multi-use basins. Research contributions are stated in Chapter 7, and research conclusions are documented in Chapter 8.

1.2. Background

Developing a water infrastructure design and management approach that accounts for nonstationarity due to the changing climate and accounts for other basin objectives is a complex problem that requires the application of systems engineering principles. Integrated Water Resources Management (IWRM) is the philosophy that water should be managed holistically and collaboratively to manage uncertainty and complexity. The key principle of IWRM is that water resources should be managed such that the benefits to all users or stakeholders are maximized without compromising the sustainability of vital ecosystems (GWP, 2000). IWRM defines a systems engineering approach to water resources management, and its principles are relevant and applicable to addressing the complex problem of managing multiple objectives within multi-use river basin under a changing climate.

The concept of IWRM has been around since the 1950s, but the implementation of an integrated design approach to infrastructure design has proven very difficult (Biswas, 2008). This is not because water practitioners do not recognize the benefits of IWRM but rather because of a lack of clear guidance and demonstration of the application of IWRM. Researchers have attempted to address this issue by coming up with case studies of the implementation of IWRM (Paulson et al., 2017; GWP, 2020). However, most of the examples of IWRM applications focus on managing the “demand” side of water use rather than the “supply” side (Mills-Novoa & Taboada Hermoza, 2017; Butterworth et al., 2010). Design and construction of water infrastructure are on the “supply” side of the spectrum. Researchers have also found that even within river basins where IWRM is professed to be practiced, exceptions are made for the construction of large-scale infrastructure projects such as those for flood control (Mills-Novoa & Taboada Hermoza, 2017).

Contrary to expectations, history indicates that interest in integrative concepts such as IWRM decreases as the complexity of water problems increases. This is because of the systemic nature of the water cycle and water uses, the multiple levels of infrastructure and governance involved, the many stakeholder groups involved, and the connections of water management with sector issues such as environmental sustainability and other societal concerns (Grigg, 2021).

Researchers have attempted to propose alternative practical approaches to IWRM that will increase the rate of adoption and implementation within basins. One such alternative is to build IWRM principles into projects, build upon existing mechanisms for participation, and organize stakeholders around water management (Butterworth et al., 2010). These are good concepts that will enhance the success of IWRM implementation.

Designing and managing water infrastructure to account for climate change is an area of ongoing research. Researchers have proposed several alternatives to the traditional design approach which assumes stationarity. The most dominant alternative approach is to maintain the current static approach and reduce the added uncertainty due to climate change by using climate forecast data (Forsee et al., 2011). An example of this approach is downscaling climate change projections from a General Circulation Model (GCM) to a local level and translating the climate projections into precipitation projections at a design input level.

Downscaling refers to the procedure used in translating known climate information at large scales to predictions at local scales (Hoar, et al. al., 2008). Although not perfect, downscaling refines spatially coarse and biased GCM output and makes them usable for local and regional climate analysis (Wilby & Wigley 1997; Huth et al. 2000; Salathe, Jr., 2002). There are generally two types of downscaling techniques: statistical and dynamic downscaling

(Lanzante et al., 2018). Statistical downscaling involves developing statistical relationships between local climate variables (such as precipitation and temperature) and large-scale (global and regional) predictors. The statistical relationship is then applied to the output of GCMs to predict local climate characteristics in the future (Hoar et al., 2008; Lanzante et al., 2018). Dynamic downscaling, on the other hand, uses the outputs from GCMs as boundary conditions for high-resolution regional climate models to simulate the future climate (Lanzante et al., 2018). GCMs use carbon emission forecasts, that are highly uncertain, as input. Downscaling climate change forecasts may lead to further uncertainty in the design variables due to the wide range and uncertainty of the climate projections (Cook et al., 2020). Statistical downscaling approaches inaccurately assume that the relationship between the GCM outputs and the regional climate data derived based on historical data is valid for future data. This assumption is referred to as statistical stationarity (Dixon et al., 2016). There is ongoing research to address the issue of statistical stationarity (Lanzante et al, 2018, Dixon et al. 2016). In addition to climatic changes, human changes to the hydrologic cycle in terms of urbanization is another source of nonstationarity (Brown, 2010).

Those studying paleoclimatology have demonstrated that proxy records found in paleological remains such as tree rings, ice rings/cores, and seashells dating hundreds of years back may be useful in estimating the range of historical variability. The approach of using paleoclimatology to define climate variability may however not be practical as paleoclimatic data is not available in all basins. One will also have to assume stationarity to apply paleoclimatic data for future planning and water infrastructure design (Brown, 2010).

Other researchers have proposed predicting future flows by loosely coupling a Global Climate Model (GCM), a regional atmospheric model, and a watershed model (Trinh et al., 2016; Adamac et al., 2010). In this approach, future climate projections simulated by the GCM are dynamically downscaled into future precipitation data using a regional climate model and bias corrected. The future precipitation data is then run through a calibrated and validated watershed model to predict hourly flow data. Statistical analysis can then be performed on the flow data to estimate a future flood frequency curve (Trinh et al., 2016). Although this approach does not fully rely on historical data, it is simulation intensive and requires simulations to be made for a long enough period (100 years for a return period of 100 years). The uncertainty within GCM projections increases the further we model into the future (IPCC, 2021), thereby decreasing the accuracy of the predicted precipitation data. Another challenge for this approach is the lack of calibration data. Even if we can calibrate the models, the calibration may not be valid in the future due to human-induced changes to the hydrological cycle in terms of increases in impervious area resulting from urbanization.

Researchers have advocated for using an adaptive management approach to mitigate against the uncertainty brought about by the non-stationary nature of climate and land use. They argue that uncertainty exists in water infrastructure design parameters due to climate change and land use changes and resource management must be flexible and able to respond as situations change (Conrad et al., 2013).

Conrad et al. (2013) define adaptive management as an iterative process for improving and revisiting management policies and practices by learning through monitoring and from outcomes of rigorously designed investigations. The generalized sequence in adaptive management involves analysis of the problem that needs to be solved, developing a management plan, implementing the plan, monitoring, and evaluating. The evaluation results are then fed back into the decision-making process to aid future planning and management.

Adaptive management can provide the framework to develop fundamental decision-making processes for adaptation in the context of uncertainty and evolving engineering and planning paradigms (Conrad et al., 2013).

Based on the above reflections on the state of the field, we can understand that there is a need for a new way of designing and managing water infrastructure that accounts for the effects of climate change by shifting the current static design paradigm to a more dynamic paradigm. The new design approach should yield quantifiable hydrological estimates that can be applied in design and management. This new approach should also be holistic and account for multiple objectives from multiple stakeholders.

1.3. Research Approach

The general research approach starts with identifying the systems engineering problem that needs to be solved, performing an extensive literature review on the current state of practice, collecting and analyzing data, developing an analysis tool and framework that can be used to test various hypotheses to develop the required approach for designing and managing water infrastructure, and finally testing and validating the new approach. The analysis tool is a hydrologic and hydraulic model that can be used to translate climate data into design and management parameters, and the framework will allow for accounting for uncertainty and multiple basin objectives and constraints. The general approach is outlined in **Figure 1**.

The approach is further developed in Chapter 2 by identifying the research questions that need to be answered, and the tasks that need to be performed to develop a new approach for designing and managing water infrastructure that accounts for nonstationarity due to climate and multiple objectives from competing stakeholders.

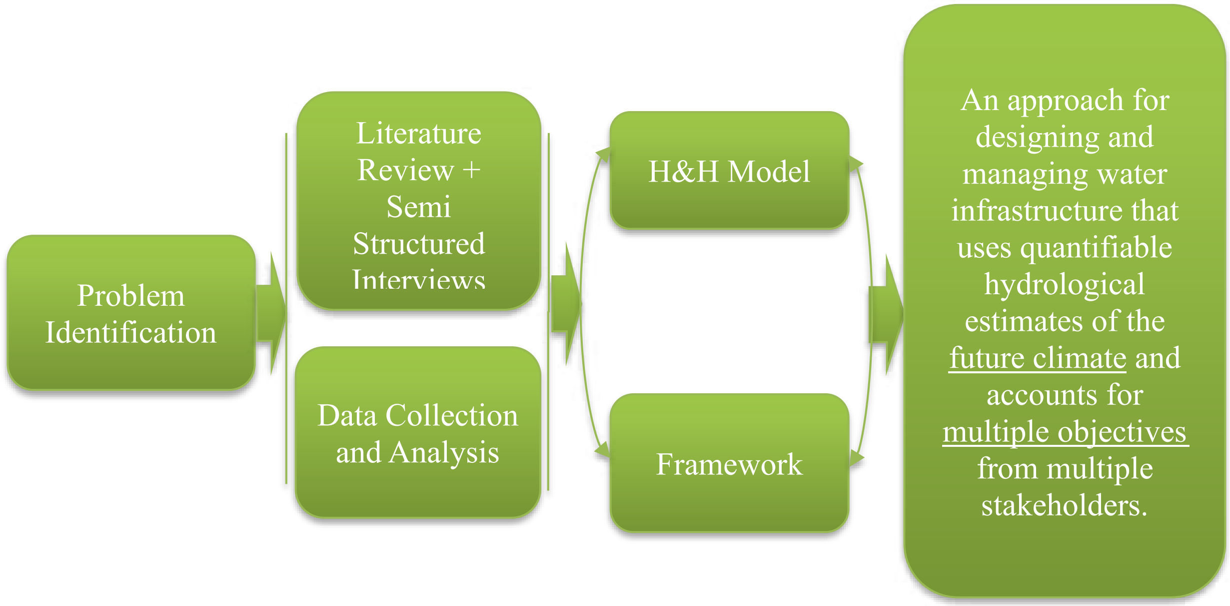


Figure 1: Linear Framework for Research

CHAPTER 2: RESEARCH QUESTIONS AND TASKS

The research questions and tasks described in this section provide the sequential framework that was used to conduct this research. These research questions and tasks build on the general research approach outlined in the preceding chapter (**Figure 1**). Each research question outlined below has a list of associated tasks that were performed to answer that question.

2.1. Research Question 1: Current Approaches for Accounting for Climate Change

What are the shortcomings of the current approaches for accounting for nonstationarity in the design and management of water infrastructure?

This research question aims to assess the various approaches for accounting for nonstationarity in the design and management of water infrastructure. As outlined in Chapter 1, traditional approaches to water infrastructure design assume that the climate is stationary. This research question assesses the adequacy and applicability of existing approaches in accounting for nonstationarity due to climate change. The tasks performed to answer this question are:

2.1.1. Task 1

Perform a literature review of existing approaches for accounting for nonstationarity due to climate change. This task involved reviewing and documenting the approaches, identifying deficiencies, and assessing their applicability to the design and management of water infrastructure.

2.1.2. Task 2

Perform a case study analysis of at least two projects that account for nonstationarity due to climate change. This task involved selecting the two projects, reviewing the projects, and documenting how climate change was accounted for. Shortcomings of the approaches used were identified and documented. This provided a deeper understanding of the current approaches for accounting for climate change in the design and management of water infrastructure.

This research question, together with the associated tasks is addressed in Chapter 3.

2.2. Research Question 2: Current Approaches for Accounting for Multi-Use Basin Objectives

What are the approaches for accounting for multi-use basin objectives in the design and management of water infrastructure?

On paper, IWRM appears to have many benefits for water infrastructure design and management and can be applied to account for competing basin objectives. However, it is not widely implemented. This research question seeks to investigate the reasons why water infrastructure design and management is still mostly considered a single-objective problem. This research question also seeks to research and document approaches for accounting for multiple basin objectives. The tasks performed to answer this question are:

2.2.1. Task 1

Perform a literature review of hindrances to implementing IWRM in water infrastructure design and management. This task involved identifying existing published literature about IWRM, reviewing it, and documenting hindrances to the adoption and application of IWRM in water infrastructure design and management.

2.2.2. Task 2

Research available approaches for accounting for competing basin objectives when designing and managing water infrastructure. The objective of accounting for other basin uses is to ensure that the design and management of the primary water infrastructure does not adversely impact other basin uses.

This research question, together with the associated tasks is addressed in Chapter 4.

2.3. Research Question 3: Approaches to Address Deficiencies of Current State of Practice

This research question has two parts and aims to provide solutions to the deficiencies of the existing approaches for accounting for nonstationarity and multiple basin objectives identified in Research Question 1 and Research Question 2. The individual research question are:

(a) How can the shortcomings of the current approaches for accounting for nonstationarity in the design and management of water infrastructure be addressed?

(b) What is the most effective and practical approach for accounting for multiple competing objectives from multiple basin uses?

These research questions seek to address the identified issues with the current design and management approach to water infrastructure. These issues are (a) not accounting for climate change and (b) not accounting for multiple basin objectives.

The field of climate change hydrologic design is still developing and yet to mature. Some great work has been done over the years and more are ongoing. For Research Question 3(a), the good portions of the current design approach are retained, and the stationary and semistationary components are replaced with non-stationary approaches that account for the changing climate. The tasks performed to answer Research Question 3(a) are:

2.3.1. Task 1 – 3(a)

As needed, conduct semi-structured interviews with expert water professionals and research advisors to identify possible solutions to accounting for nonstationarity including adaptive design and management strategies. The goal of this task is to solicit ideas about how analytical methods and adaptive management practices have been implemented in the past and how they can be implemented in multi-objective basins to account for uncertainty in climate projections and socio-physical changes such as basin objectives and land use changes.

2.3.2. Task 2 – 3(a)

Identify the sources of uncertainty in the design and management of water infrastructure in multi-use basins and the baseline conditions for all the identified sources of uncertainty.

2.3.3. Task 3 – 3(a)

Acquire climate change, and hydrologic and hydraulic data for a case study basin. This is a data collection task that involves collecting topographical data, land use data, soil data, reservoir operations data, and all other data that is needed to develop a hydrologic and hydraulic (H&H) model for a case study basin. Sources of data included state and federal agencies such as the National Atmospheric and Oceanographic Agency (NOAA), the United States Geological Survey (USGS), clients, private companies such as Duke Energy, and academic institutions.

2.3.4. Task 4 – 3(a)

Build a hydrologic and hydraulic model using the United States Army Corps of Engineers HEC-RAS software (USACE, 2021) of a representative multi-use basin that can be used in testing alternative approaches to accounting for climate change in hydrologic design. The model was based on the baseline conditions identified in Task 2. This task involved using the data collected to build the H&H model.

This research question, together with the associated tasks, is addressed in Chapter 3 and Chapter 5.

The tasks to be performed to answer Research Question 3(b) are:

2.3.5. Task 1 – 3(b)

Conduct semi-structured interviews with expert water professionals and research advisors to identify approaches for accounting for multiple basin objectives including adaptive design and management strategies. The goal of this task is to solicit ideas about how analytical methods and adaptive management practices have been implemented in the past and how they can be implemented in multi-objective basins to account for uncertainty in climate projections and socio-physical changes such as basin objectives and land use changes.

2.3.6. Task 2 – 3(b)

Develop an adaptive management framework to allow for future updates to design and management based on increased forecast accuracy in the future and changing basin objectives.

This research question, together with the associated tasks is addressed in Chapter 4.

2.4. Research Question 4: Approach Testing and Verification

How does the new approach that accounts for nonstationarity and multiple objectives compare to the traditional approach?

The previous research questions provide insight and the building blocks to formulate a new approach that addresses the issue of nonstationarity in terms of climate change and accounts for multiple basin objectives. The success of the new approach will be determined by whether it addresses the previously identified issues and its applicability to the water resources industry. The new approach's success is defined based on the following:

1. Ability to cost-effectively use climate change projections. Cost-effectiveness is defined as the ratio of the cost to account for climate change and the total cost of the project. The smaller the ratio, the more cost-effective the approach.

2. Applicability to all basins and projects, irrespective of geographic location, size, or uses.

3. Ability to independently duplicate the results produced by the approach. Different engineers using the documented approach should arrive at similar conclusions. The approach must consist of minimal subjective components.

This research question aims to document the new approach, demonstrate how it addresses the previously identified issues, demonstrate how it can be applied in multi-use basins, and how the results from using the new approach compare to results from using the traditional approach. The tasks to be performed to answer this Research Question are:

2.4.1. Task 1

Build on the hydrologic model created under research question 3 to develop a research tool (climate + Adaptive management framework) that is formulated based on the ability to test multiple hypotheses of the research questions. The adaptive management framework feeds into the hydrologic model and vice versa. This is an iterative process until a design and management approach that addresses all the issues previously identified is obtained. When available, feedback from stakeholders was used to determine whether the new approach addresses the previously identified issues.

2.4.2. Task 2

Compare and contrast the new approach to the traditional approach and document findings and recommendations. The new approach was compared to the traditional approach, and the benefits, compared to the traditional approach, were documented. Areas of improvement and additional research areas were also be identified as needed.

CHAPTER 3: EVALUATION OF NONSTATIONARITY METHODS

This chapter describes the current state of practice, summarizes the existing literature on methods for accounting for nonstationarity, assesses each method against predetermined criteria for addressing climate change uncertainty in water infrastructure design, and recommends the most appropriate approach for accounting for nonstationarity due to climate change in the design and management of water infrastructure. This chapter addresses Research Questions 1 and 3(a), which are restated here:

Research Question 1 - What are the shortcomings of the current approaches for accounting for nonstationarity in the design and management of water infrastructure?

Research Question 3(a) - How can the shortcomings of the current approaches for accounting for nonstationarity in the design and management of water infrastructure be addressed?

3.1. Current State of Practice

The current state of practice is predominantly based on the assumption of a stationary climate. As noted in Chapter 1, the practice of basing the hydrologic design of water infrastructure on principles where climate is stationary and future conditions can be represented by variances in historical trends is no longer appropriate given the preponderance of climate studies predicting a varied and uncertain climate future (Brown, 2010; Milly et al., 2008; IPCC, 2001; IPCC, 2014). This varied climate future is expected to increase the severity of extreme hydrologic events in many parts of the world (Christensen & Busuioc, 2007). Rising temperatures are also likely to result in more intense storm surges, requiring more substantial flood control structures (IPCC, 2014; IPCC, 2021). Static approaches for water infrastructure design may result in failed infrastructure investments that could lead to loss of lives, property and stormwater pollution, and sanitation issues that present adverse conditions for public health (IPCC, 2014; IPCC, 2021). Therefore, a shift to a dynamic approach that accounts for the changing climate is urgently needed and frequently argued (Garrote, L., 2017).

In response, research on designing and managing water resources infrastructure to account for climate change has focused on improving climate forecast data by downscaling climate change projections from a General Circulation Model (GCM) to a local level and translating the climate projections into precipitation projections at a design input level (Forsee et al., 2011; Hoar et al., 2008; Islam, A. S. et al., 2018). It is argued that downscaling refines spatially coarse and biased GCM output and makes them usable for local and regional climate analysis (Salathé Jr., 2003). The climate change-informed data is then used in design and management decisions. However, there are two limitations to this approach.

First, downscaling techniques routinely rely upon developing statistical relationships between local climate variables (such as precipitation and temperature) and large-scale (global and regional) predictors (Lanzante et al., 2018). The statistical relationship is then applied to the output of GCMs to predict local climate characteristics in the future (Hoar et al., 2008; Lanzante et al., 2018). Uncertainties in the input variables are carried through and the resulting downscaled climate change forecasts may lead to further uncertainty in the design variables due to the wide range and uncertainty of the input, for instance, carbon emission projections (Cook et al., 2020).

Second, downscaling approaches assume that the relationship between the GCM outputs and the regional climate data derived based on historical data is valid for future predictions (Dixon et al., 2016). The assumption that the relationship between the GCM outputs and regional climate data is constant (statistical stationarity) is not always supported as changes in the environment, such as urbanization, may alter the relationship between the GCM outputs and the regional climate data.

To address the limitations of climate change projections and GCM downscaling methods, this research systematically reviewed the literature and identified five approaches for accounting for climate change in the design and management of water infrastructure, outlining the strengths and weaknesses of each approach and assessing the applicability of each approach to water infrastructure design. Each approach proposes methods to reduce the errors in the resulting infrastructure design, recognizing the inherent uncertainty in climate data and GCM outputs available for decision-making.

This chapter is structured as follows: the first section describes the research methodology, including the selection of literature, approaches, and case studies. The second section provides a review of available approaches and gives a summary of approaches for accounting for climate change in water infrastructure design in literature and selected case studies. The third section presents a discussion of the approaches and implications for future design, followed by a conclusion in the fourth section.

The contribution of this study is holistic. First, in meeting its aim, this study offers a summary of approaches to designing more climate-resilient water infrastructure. Second, it extends the literature and knowledge of applicable approaches, allowing water managers to consider a broader suite of management options with stakeholders. Third, this is the first comparative review of uncertainty approaches for addressing nonstationarity in water infrastructure design.

3.2. Methods

To select the approaches for accounting for climate change in water infrastructure, and subsequently select case studies that demonstrate the applicability of such methods, a literature review was conducted between April and June 2022. Relevant literature was retrieved using Primo Search and Google Scholar. The keywords/phrases used to retrieve publications within these search engines/libraries were *climate change on precipitation*, *nonstationarity*, and *water infrastructure design*. The literature selection focused on literature that discussed the application of methods for addressing nonstationary as opposed to literature that only utilized a method.

Following stakeholder consultation with water industry experts on current approaches and challenges for addressing climate change, literature was examined against four criteria for addressing climate change uncertainty in water infrastructure design. (1) The applicability of the approach to water infrastructure design; (2) the reduction in uncertainty achieved by implementing the approach; (3) the adaptability of the approach to various design conditions and basins; and (4) the computational cost-effectiveness of implementing the approach.

The criterion of applicability refers to whether the approach can be applied in the design and management of water infrastructure. Suitable approaches should yield quantifiable hydrological estimates that can serve as the basis for designing and managing water infrastructure and supporting water industry applications and should be reproducible (should produce similar results irrespective of user).

The second criterion, reduction in uncertainty, addresses how the approach reduces the challenge of including uncertainty in the decision-making process. Water practitioners and managers face management issues ranging from insufficient hydrologic record lengths, natural variability blended with anthropogenic-induced changes, inconclusive results from climate change studies, and the effect of future climatic changes on hydrologic design (Stakhiv, 2011). It is, therefore, important that water practitioners have accurate hydrological estimates of the future climate to make reliable decisions. The approaches were reviewed for how well they eliminate or accurately quantify the uncertainty regarding climate change projections and downscaling methods. Having a quantified estimate of uncertainty aids with decision-making.

The third criterion, adaptability, refers to how well the approach can be applied to basins of different sizes and uses and in various geographic regions. Approaches that are specific to water infrastructure types and regions were viewed as lacking adaptability whereas those approaches that could be applied broadly to all basins would have more universal application and be of use to the global water community.

The final criterion is cost. Cost is an often-cited factor in the acceptability and usefulness of an approach intended to be used by water practitioners to design and manage water infrastructure. For this research, cost is defined as the relative computational cost-effectiveness of an approach in terms of effort and funds expended in implementing the approach. Cost was not calculated but qualitatively assessed in the review based on industry stakeholder consultation.

After examining where the articles met the criteria, approaches for accounting for climate change in water infrastructure were identified for further review. **Figure 2** describes the selection and review process. Only literature that addressed multiple criteria were included in the final selection. The distribution of the selected publications by year is shown in **Figure 3**.

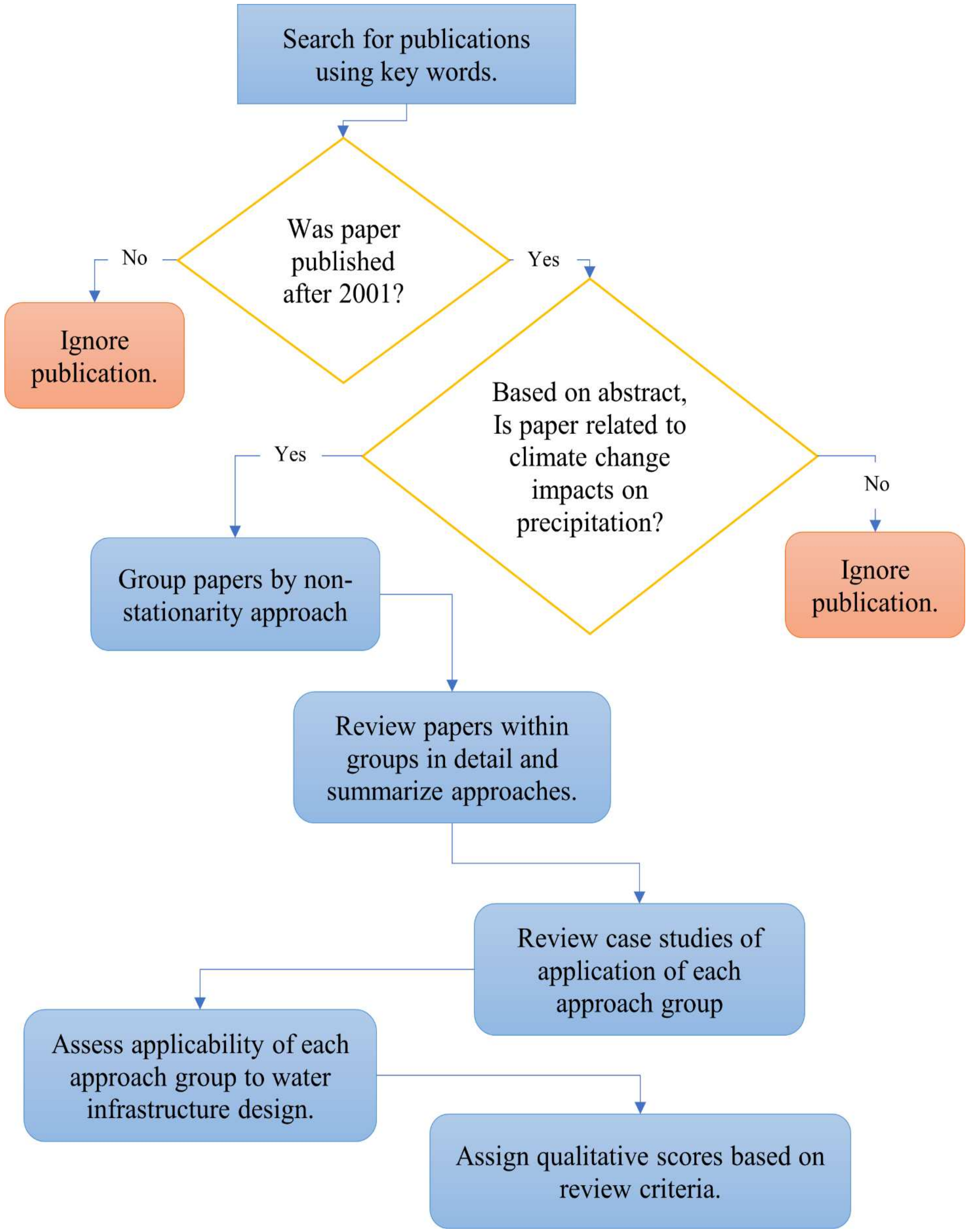


Figure 2: Literature Selection and Review Approach Flowchart

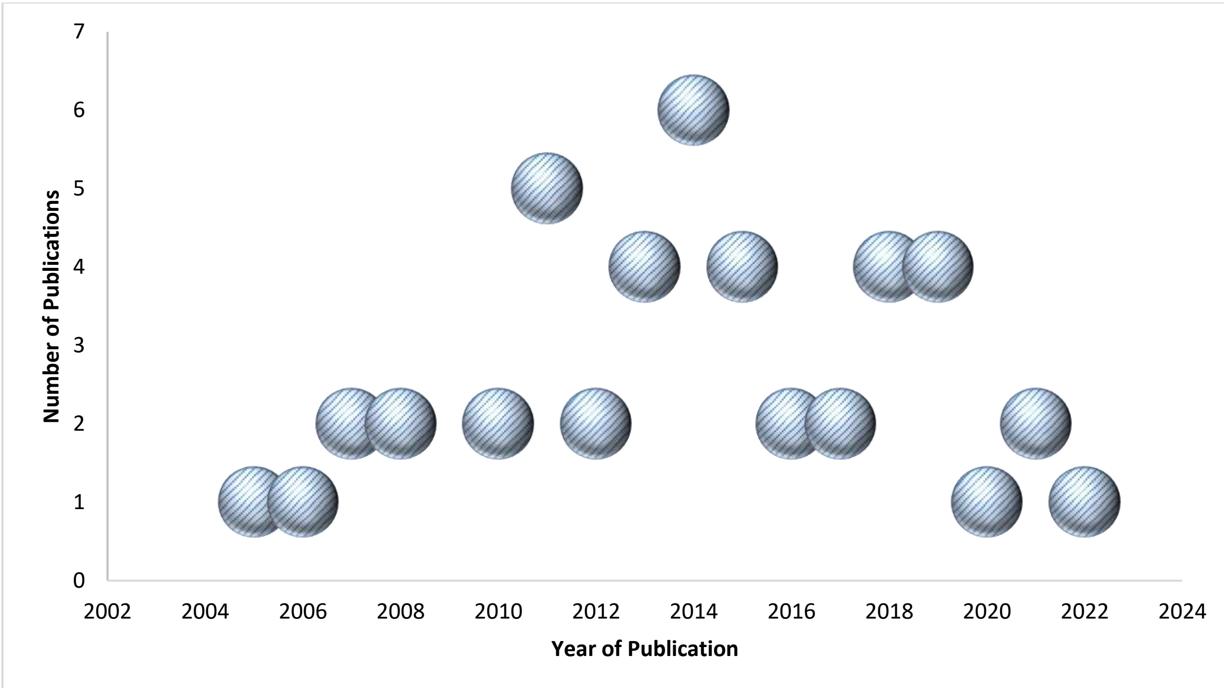


Figure 3: Distribution of Selected Publications by Year

Case studies were selected from published and grey literature (in academia, government agencies, and the engineering industry) and demonstrate how the approaches described in this chapter have been applied to watersheds in arid and temperate parts of the United States. A descriptive review of the case studies was conducted to gather insights into the strengths and weaknesses of the methods as they relate to the four criteria above.

Literature and case studies were limited to publications after 2001 to correspond with the third Intergovernmental Panel on Climate Change report detailing the scientific basis for adapting to the effects of global climate change (IPCC, 2001). The third IPCC report presents observations from complex physics-based climate models that indicate confidence in the projections was on the rise and created a sound footing for the need to address nonstationarity effects. The 20+ year period provided an extensive review timeframe to suggest insights about how the knowledge and perspective on the approaches for indoctrinating climate change in water infrastructure design have evolved.

3.3. Review Approaches

From the selected literature, five approaches for accounting for climate change uncertainty were identified through a key theme analysis based on frequency of occurrence: adaptive management, inverse climate change impact method, machine learning, flood frequency analysis, and soft computing approaches. **Table 1** and **Figure 4** present the results of the literature analysis.

Table 1: Strategies, citations, and preliminary review analysis results

Strategy	**Review and summary of literature approach theme(s)**	**# of occurrences**	**% of occurrences**
1. Adaptive Management	Defining the need for new management approaches, adaptation, or management barriers	8	18%
2. Inverse Climate Change Impact	Discussion of climate impact assessment, reverse engineering, inverse modeling, and climate change modeling	2	4%
3. Machine Learning	Discussion of machine learning models, advanced computational approaches, and applications in water infrastructure design	6	13%
4. Adjusted Flood Frequency Analysis	Trends in flood frequency analysis, prediction, statistical downscaling, and application of Climate change forecast data	3	7%
5. Soft Computing	Discussion of statistical approaches for quantifying uncertainty due to climate non-stationarity.	4	9%
6. Mixed	Discussion of multiple methods to include computational forecasts, management, and modeling.	8	18%
7. Other	Other discussions of approaches including problem identification, and case studies	14	31%
Total		45	100%

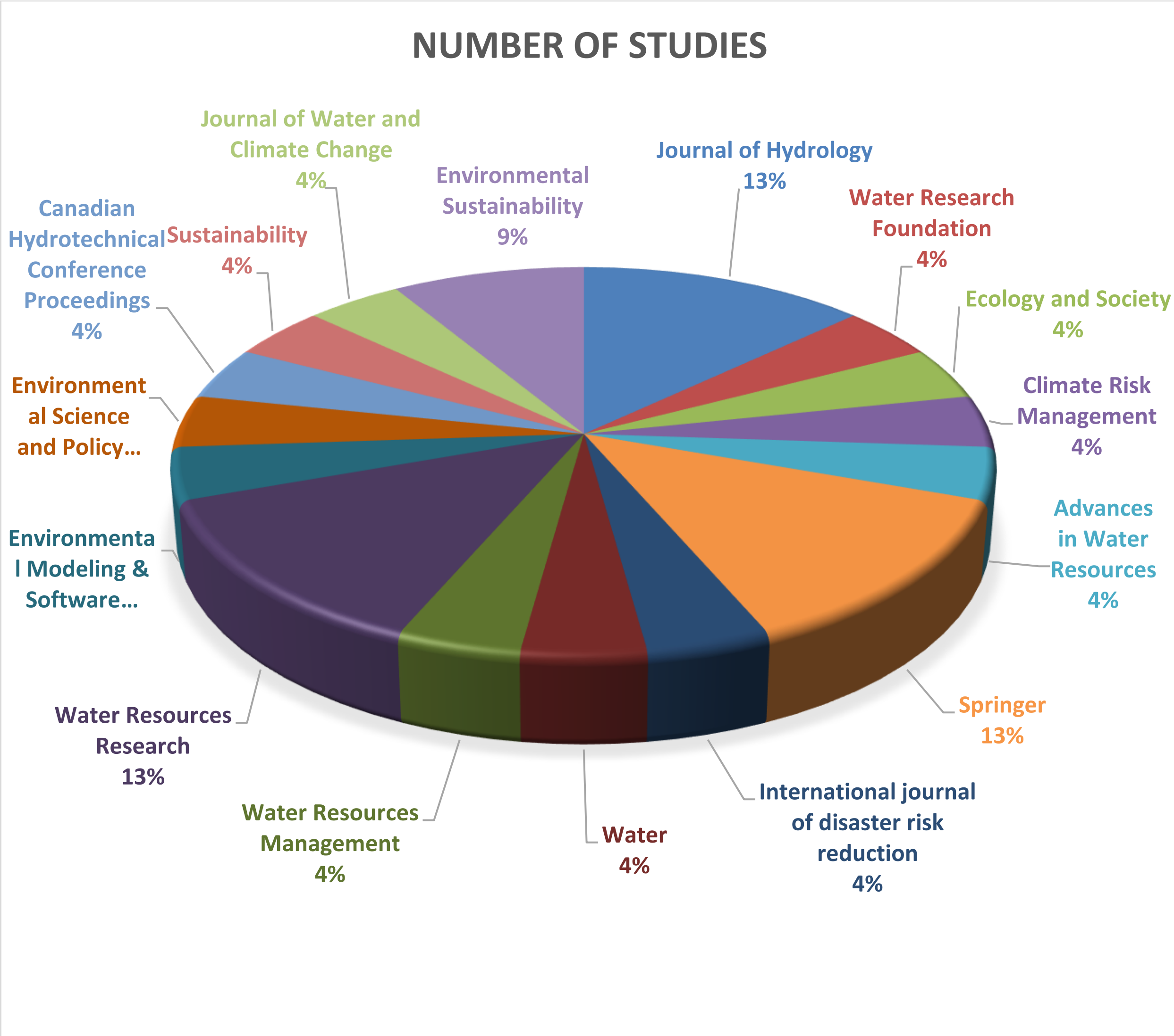


Figure 4: The distribution of research articles in the scope of this study

3.3.1. Adaptive Management Approach

Conrad et al. (2013) define adaptive management in a water context as an iterative process for improving and revisiting management policies and practices by learning through monitoring and from outcomes of rigorously designed investigations. The generalized sequence in adaptive management involves analysis of the problem that needs to be solved, developing a management plan that includes treatments or responses to the problem, implementing the plan, and monitoring, evaluating, and adjusting the plan based on observation. The evaluation results are then fed back into the decision-making process to aid future planning and management. Proponents of adaptive management argue the framework provides a flexible decision-making process for adapting to uncertainty and allows for evolving engineering and planning paradigms to increase flexibility in infrastructure design (Allan, C., et al., 2013; Kundzewicz, Z. W., et al., 2018; Pahl-Wostl, 2008; Conrad et al., 2013).

Adaptive management approaches mitigate the uncertainty brought about by the non-stationary nature of climate by continually adjusting water infrastructure design and management decisions based on improvements in climate change data and methods. Uncertainty exists in water infrastructure design parameters due to climate change. Information about the future climate needed for the design of water infrastructure will always be incomplete. Adaptive management provides a flexible approach to managing uncertainty and allows water practitioners to respond as situations change (Pahl-Wostl et al., 2007). Adaptive management supports water managers in adjusting future actions based on answers to questions such as: To what extent were management goals met? How accurate were past predictions? How valid are the assumptions about the impacts of climate change? Did the actions have the desired effect? And what additional data and information is required to evaluate future actions? Adaptive management is a rigorous tool for learning through intentionally designed management actions and requires constant monitoring and learning to formulate adaptive adjustments as added information becomes available (Conrad et al., 2013).

Adaptive management is widely used in the fields of forestry, ecosystem restoration and others (see Allen & Garmestani, 2015; Fernandez-Gimenez et al., 2008). However, it has not yet been widely accepted in water infrastructure design and management and may face institutional and behavioral challenges during implementation (Varady, Robert G. et al., 2016). Adaptive management may also require changes to the built infrastructure and such actions are undesirable for some water practitioners. Additional challenges and barriers in the implementation of adaptive management include: institutional concerns in admitting uncertainty cannot be overcome; challenges securing the additional resources required to design robust experimental, management activities and monitoring schemes; difficulties maintaining long-term continuity of funding; additional costs for model development, assessment and monitoring; difficulty in detecting and documenting success; political pressure to alter management plans; institutional inertia ("path dependency") and inflexibility ("lock-in"); and institutional arrangements that do not foster activities with long-term time frames (Conrad et al., 2013).

3.3.2. Inverse Climate Change Impact Approach

Inverse climate change impact approaches assess the influences of climate change in terms of hydrological extremes on infrastructure design by identifying the critical hydrologic exposures, such as floods and droughts, that may lead to failures of the hydrological system and transforming the hydrological exposure into corresponding meteorological conditions by means of hydrological models which are linked with future climate scenarios generated by a weather generating algorithm coupled with GCM outputs (Cunderlik & Simonovic, 2007). These approaches allow for the evaluation of the performance of water infrastructure independently of climate change projections (Guo et al., 2018).

These approaches aim to mitigate the uncertainty brought about by the non-stationary nature of climate by providing conservative estimates of the extreme events that result in the failure of the infrastructure. For instance, Cunderlik & Simonovic (2007) note that inverse climate change impact approaches are advantageous because they focus on specific existing and anticipated future water resource problems, have a direct link with the end-user, and allow for easy updating, when new and improved GCM outputs become available.

The structure behind inverse climate change impact approaches involves identifying critical local hydrologic exposures to existing or future water resource systems. Then, a hydrologic model is used to transform hydrologic exposures through extreme precipitation events and dry spells over an extended period. The critical meteorological conditions are then simulated under existing and future climatic scenarios using a weather generator that is linked with GCMs and an ensemble of simulations that reflect possible future climatic conditions. Weather generators produce ensembles of climate scenarios that can be sampled at yearly, monthly, daily, or hourly timescales. The result of this process is information about the frequency of the critical meteorological events that are likely to result in the failure of the hydrological system (Cunderlik & Simonovic, 2007; Guo et al., 2018).

In summary, this approach addresses uncertainty through a methodological process by (1) identifying the critical flooding depths that will result in failure of a hydrologic system, (2) estimating the rainfall depths and durations that will result in the critical flooding depths using a hydrologic model, (3) estimating the combinations of meteorological conditions (present and future) that can produce the critical rainfall depths and durations using weather generators and GCM outputs, and (4) estimating the likelihood and frequency of such meteorological conditions.

3.3.3. Machine and Deep Learning Approach

Physical and statistical models, which are the most common forms of modeling climate, atmospheric, and hydrological systems, have shortcomings such as accuracy, weakness in uncertainty analysis, high computation cost, and the need for a comprehensive amount of data

(Ardabili et al., 2020; Mosavi et al., 2018). The data requirements for physical models make them unsuitable for use in short-term prediction (Mosavi et al., 2018).

Surrogate modeling techniques such as interpolation, regression analysis, and artificial intelligence may provide a means for utilizing complex climate models in decision-making environments. Machine learning and deep learning methods have been shown to be able to overcome high computational requirements and uncertainties in modeling through their efficient computation and intelligence (Farzin, S. & Anaraki, V., 2021; Ardabili et al., 2020; Mosavi et al., 2018).

Mosavi et al. (2018) define Machine Learning as a field of artificial intelligence (AI) used to induce regularities and patterns, providing easier implementation with low computation cost, as well as fast training, validation, testing, and evaluation, with high performance compared to physical models, and relatively less complexity. Machine learning methods can numerically formulate flood nonlinearity solely based on historical data without requiring knowledge about the underlying physical processes, therefore providing an appropriate surrogate for physical models. Machine learning methods are also quicker to develop with minimal inputs (Mosavi et al., 2018). Machine and deep learning approaches mitigate against the uncertainty brought about by the non-stationary nature of climate by better characterizing the level of uncertainty, thereby making it possible to account for the level of uncertainty in decision-making.

Machine learning methods can be classified as tree-based, support vector machine (SVM), neural network-based, and hybrids and ensembles. Tree-based ensemble methods include Random Forest (RF), M5tree, gradient boosting decision tree, and extreme gradient boosting. RF has been shown to have higher accuracy when compared to other methods (Kadkhodazadeh et al., 2022; Ardabili et al., 2020). Deep learning techniques are a significant part of machine learning methods

(Ardabili et al., 2020).

The main shortcoming of machine learning and deep learning techniques noted in literature is the extensive amount of data needed to accurately train them. Machine learning and deep learning, a subset of machine learning, techniques may also not accurately account for future variations in climate due to their reliance on historical data. As noted by Mosavi et al. (2018), machine learning methods learn to predict the target task based on past data. These methods are only as good as their training, so it is essential that the training data be as robust as possible. If the data is scarce or does not cover a variety of tasks, their learning falls short, and hence, they cannot perform well when they are put to work.

Despite the data limitations, applications of machine learning methods for predicting future floods under the uncertainty of climate change have proved to be cost-effective and to increase overall predictive capacity (Mosavi et al., 2018). Applications include modeling the effects of climate and land use changes on flood susceptibility areas in the Tajan watershed (Avand and Moradi, 2021), developing flood prediction for urban management (Motta et al., 2020), as a surrogate for high-resolution output from MODFLOW, a modular hydrologic model (Miro et al., 2021), runoff prediction (Farzin, S., & Valikhan Anaraki, M., 2021), flood frequency analysis (Anaraki, V., et al., 2020) and for predicting evapotranspiration (Kadkhodazadeh et al., 2022).

3.3.4. Flood Frequency / Statistical Modeling Methods Approach

Gilroy and McCuen (2012) note that climate change is expected to affect flood magnitudes by changing precipitation patterns and urbanization affects flood magnitudes by changing the runoff for each precipitation event. In response, Gilroy and McCuen (2012) developed a method to adjust a flood record for future nonstationary conditions based on two factors: climate change and urbanization. The goal of their study was to apply a nonstationary peak discharge record to one that is stationary for a selected design year, with the added advantage that the adjusted stationary record can reflect future climate conditions and urbanization (Gilroy & McCuen, 2012). Adjustment factors are developed for both the climate change and urbanization components in response to precipitation projections from selected GCMs. The goal is to estimate the expected temporal change in heavy rainfall intensity over time for a specified climate change scenario and then apply the estimated change to the observed precipitation record (Gilroy & McCuen, 2012). The process is repeated until each peak discharge event within the measured flood series is adjusted to the urbanization and climate change conditions of the design year (Gilroy & McCuen, 2012).

The method developed by Gilroy and McCuen (2012) allows for the development of a flood frequency analysis using data adjusted to reflect future climate conditions and urbanization. The resulting flood estimates reflect the stationarity of the underlying distribution. The adjustment factor method reflects the expected change in peak discharge based on both urbanization and climate change and has the advantage of adaptability in that the adjustment factor can be updated as new climate change data become more available and more accurate or more complex hydrologic models are selected (Gilroy & McCuen, 2012).

Similarly, Solaiman and Simonovic (2011) describe an approach for updating rainfall intensity-duration-frequency (IDF) curves to account for climate change. The approach involves determining possible realizations of future climate using downscaled outputs from GCMs; fitting annual maximum series of rainfall to Gumbel distribution to develop IDF curves for 1, 2-, 6-, 12- and 24-hour durations for 2, 5, 10, 25, 50 and 100 years of return periods; estimating the associated uncertainties using nonparametric kernel estimation approach; and developing an IDF curve based on a probabilistic approach (Solaiman & Simonovic, 2011). The overall method involves adjusting rainfall records to reflect the long-term effects of climate change, transforming rainfall to runoff, and adjusting the peak discharge to account for future urbanization.

Flood frequency approaches may mitigate against the uncertainty brought about by the non-stationary nature of climate by employing an ensemble of climate change projections in determining the expected change in the frequency of a given storm event. Solaiman and Simonovic (2011) noted that using a multi-model approach, rather than a single scenario is encouraged due to the inherent uncertainties associated with different GCMs. GCMs represent physical processes in the atmosphere, ocean, cryosphere and land surface and are the most advanced tools available for simulating the response of the global climate system to increasing greenhouse gas concentrations. GCMs offer only possibilities of future climate patterns in differing socioeconomic conditions depending on the continual growth of population, increased carbon dioxide emission, rate of urbanization, etc. Outputs from GCMs, thus, should not be considered as the forecasts of future climate conditions. The authors argue that for a comprehensive assessment of future changes, it is important to use collective information by utilizing all available GCMs and synthesizing the projections and uncertainties in a probabilistic manner.

3.3.5. Soft-Computing (Fuzzy Set Theory, Extreme Value Theory, Bayesian methods) Approach

Soft computing approaches mitigate against the uncertainty brought about by the non-stationary nature of climate by providing a means to characterize and quantify the level of uncertainty, thereby making it possible to account for the level of uncertainty in decision-making. For instance, Steinschneider et al. (2012) note that Bayesian methods provide a formal mechanism to characterize the error in hydrologic model predictions, along with uncertainties surrounding parameterization.

Mondal and Mujumbar (2015) noted that the low resolution of GCMs and their inability to simulate localized processes necessitate the use of statistical downscaling models, which are often used together with physically based hydrologic models for the generation of streamflow projections. This approach usually leads to projections of hydrological extremes with low to medium confidence because of the limitations of climate models and the lack of sufficient observations at smaller scales. Extreme value theory (EVT) provides the theoretical basis for modeling extreme events. Nonstationary extensions to the traditional stationary extreme value models enable the incorporation of effects of one or more physically based covariates in the parameters of the statistical extreme value model. Nonstationary extreme value distributions can be applied to study climate change extremes. Mondal and Mujumbar (2015) used a two-component nonstationary peak-over threshold (POT) approach of the EVT statistical model based on the Poisson-Generalized Pareto (Poisson-GP) distribution to model changes in the frequency and intensity of droughts.

Steinschneider et al. (2012) proposed a Bayesian formulation for rainfall-runoff modeling that can be used to help quantify uncertainties in a climate change impact analysis. Steinschneider et al. (2012) note that direct use of downscaled, multi-model GCM output as forcing data for climate change assessments can only generate a lower bound on the maximum range of future climate uncertainty. Since GCM simulations over the historical record do not fully explore the multiple sources of uncertainty at play, it may prove difficult, if not impossible, to develop a satisfying error model and bracket the true uncertainty of future climate projections. The objective of the formulation was to demonstrate how future climate uncertainties can be nested in a framework aimed at quantifying the total uncertainty in future hydrologic projections. Steinschneider et al. (2012) accounted for different sources of hydrologic model uncertainty using

Bayesian modeling. They formally characterized the distribution of model residuals to quantify predictive skill and used Markov chain Monte Carlo sampling to infer the posterior distributions of both hydrologic and error model parameters. They then integrated parameter and residual error uncertainties to develop reliable prediction intervals for streamflow estimates. They then extended the Bayesian hydrologic modeling framework to a climate change impact assessment. They downscaled ensembles of baseline and future climate from GCMs and used them to drive simulations of streamflow over parameters drawn from the posterior space. They calculated time series of streamflow statistics from baseline and future ensembles of simulated flows and integrated uncertainties in hydrologic model response, sampling error, and the range of future climate projections to help determine the level of confidence associated with hydrologic alteration between baseline and future climate regimes. Their formulation can be used to emphasize the importance of prediction error in uncertainty analyses under climate change and highlight the complex interactions between different sources of modeling uncertainty.

Teegavarapu (2010) observed that results from climate change models for hydrologic analysis are highly uncertain due to the shortcomings and capabilities of general circulation models (GCMs) and the different coupling methods used at various levels of scales in the integration of GCMs and hydrologic models. Although a lot of effort has been put into improving climate change predictions, substantial uncertainty remains in trends of hydrological variables because of large regional differences, gaps in spatial coverage, and temporal limitations of data. Teegavarapu (2010) highlights several issues related to climate change and its impact on water resource management and addresses a few by providing methodologies that can help to deal with climate change in water resources management models. Teegavarapu (2010) proposed a fuzzy mathematical programming framework to aid decision-makers in including their degree of uncertainty in their climate change predictions and processes. Teegavarapu (2010) notes that membership functions are generally defined on fuzzy sets to describe the degrees of truth on a scale [0-1] for a physical quantity or a linguistic variable. The scale is used to characterize the uncertainty or vagueness associated with the definition of the variable as perceived by humans. Fuzzy membership functions are used to model the decision maker's preferences attached to possible variations in hydrologic inputs due to climate change.

Teegavarapu (2013) notes that soft computing approaches composed of fuzzy rule-based inference systems and neuro-fuzzy methods and their derivatives are ideally applicable for situations in which system parameters are imprecise and vague and are primarily useful for adaptive control under uncertain decision-making environments. Teegavarapu (2013) notes that precipitation, as an important component of the hydrologic cycle, bears a significant influence on hydrologic design and water resources management. The uncertainties associated with future climate change, coupled with limitations of climate change models and uncertainties in projections, and our inability to quantify these, introduce additional complexities in hydrologic design using future precipitation extremes. Teegavarapu (2013) proposed a new optimal compromise hydrologic design of a storm sewer system using a fuzzy mixed integer nonlinear mathematical programming model with discrete, binary variables and logical constraints.

The model proposed by Teegavarapu (2013) incorporates the preferences of hydrologists toward possible changes in future precipitation extremes within an optimization formulation for a hypothetical storm sewer system. Linear fuzzy membership functions are used to describe decreasing preferences toward cost. Also, preferences toward changes in future precipitation extremes are modeled using linear, nonlinear (exponential, Gaussian), and triangular membership functions. A fuzzy nonlinear optimization model provides a climate change-sensitive hydrologic design that considers compromise between current and future precipitation extremes by handling the preferences. Discrete values of optimal decision variables provided by the model aid in the implementation of optimal design solutions in field applications.

3.4. Case Studies

This section describes three case studies of the application of climate change forecasts in the design of water infrastructure. The selection of case studies was limited to those completed from 2001 to the present to focus on the application of the most recent advances in climate change modeling that rely on relatively reliable GCM outputs.

(1) Stormwater Infrastructure Design in Las Vegas

Forsee and Ahmad (2011) analyzed the projected changes in design-storm depths and the resulting effects on storm-water infrastructure design for an arid watershed in the Las Vegas delta using the updated flood frequency approach. They used multipliers that represent the percentage change in climate to transpose projected future changes in climate onto point precipitation data. Foresee and Ahmed (2011) initially based the projected changes in design-storm depths on five North American Regional Climate Change Assessment Program (NARCCAP) data sets. The NARCCAP data sets have a 50 km spatial resolution and provide precipitation on a 3-hourly temporal resolution. The next step was to use climate change projections from GCMs and Regional Climate Models (RCMs) that reproduce historic precipitation statistics to calculate delta-change factors. The delta-change factors were then applied to design-storm depths, enabling the analysis of storm-water infrastructure under different scenarios. The time span used was 30 years for both historical (1971–2000) and future (2041–2070) scenarios.

Forsee and Ahmed (2011) utilized the existing Pittman HEC-HMS storm-water model for their analysis. In the Pittman HEC-HMS storm-water model, each subbasin has a specified 6-hour 100-year point depth, which was obtained from NOAA Atlas II estimates of the 6-hour 100-year depth. The Pittman HEC-HMS model was run with baseline precipitation data. The precipitation data for each of the sub-basins were then adjusted based on the delta-change factors and then rerun to estimate the impact of climate change on the hydraulic design of stormwater infrastructure within the basin.

(2) Assessment of Impacts of Climate Change on Stormwater Infrastructure in Washington State

Our case study exploration in Washington State demonstrates the application of the updated flood frequency analysis approach. Rosenberg et al. (2010) examined both historical precipitation records and simulations of future rainfall to evaluate past and prospective changes in the probability distributions of precipitation extremes in the Thornton Creek and Juanita Creek watersheds. Rosenberg et al. (2010) based their historical analyses on hourly precipitation records for the period 1949–2007 from weather stations surrounding the Puget Sound region (including Seattle, Tacoma, and Olympia), the Vancouver (WA) region (including Portland, OR), and the Spokane region. Rosenberg et al. (2010) simulated changes in future precipitation changes using two runs of the Weather Research and Forecast regional climate model (RCM) for the time periods 1970–2000 and 2020–2050, statistically downscaled from the ECHAM5 and CCSM3 Global Climate Models and bias-corrected against the SeaTac Airport rainfall record. Rosenberg et al. (2010) used the bias-corrected and statistically downscaled ("BCSD") hourly precipitation sequences as input to the Hydrological Simulation Program - FORTRAN (HSPF) model to simulate streamflow in two urban watersheds in central Puget Sound. HSPF is a Fortran-based hydrologic simulation program that was developed under contract and is maintained by the U.S.

Environmental Protection Agency. HSPF is a lumped-parameter model that simulates discharge at user-selected points along a channel network from a time series of meteorological variables (notably, rainfall, temperature, and solar radiation) and a characterization of hydrologic variables (such as infiltration capacity and soil water-holding capacity) that are typically averaged over many hectares or square kilometers (Rosenberg et al., 2010).

Rosenberg et al. (2010) used the BCSD precipitation data for the periods 1970–2000 and 2020–2050 as input to HSPF to reconstitute historical streamflows and predict future streamflows in the Thornton Creek and Juanita Creek watersheds. Additionally, Rosenberg et al. (2010) used HSPF to evaluate differences in 1970–2000 simulated flows as forced by both the historical rainfall record and the BCSD rainfall. Their results from both the Thornton Creek and Juanita Creek modeling runs did not indicate significant differences in streamflow biases from the direct comparison of observed and simulated rainfall records.

Rosenberg et al. (2010) then simulated streamflows for both watersheds and each of the two RCM runs using the BCSD rainfall for the periods 1970–2000 and 2020–2050. They fitted Log-Pearson Type 3 distributions to the resulting annual maxima and tested for statistical significance using the Komolgorov-Smirnov, Wilcoxon rank-sum, and Mann-Kendall tests at a two-sided α of 0.05. Their results at the mouths of both watersheds indicate increases in streamflows for both RCM runs and all recurrence intervals.

(3) Effects of Climate Change on Urban Stormwater Infrastructures in the Las Vegas Valley

Thakali et al. (2016) conducted a study to assess the potential effects of climate change on existing infrastructure systems for urban stormwater infrastructure in Las Vegas Valley using the updated flood frequency approach. Thakali et al. (2016) used historical and projected future precipitation from all the available GCM-driven and RCM-projected precipitation data from

NARCCAP to calculate the deviation between historical and future design storms and used the data that represents the historical precipitation to calculate delta-change factors, which were applied to the design storm depths.

In their study, Thakali et al. used regional frequency analysis (RFA) based on L-moments (a linear combination of probability-weighted moments) to calculate the design storm depth (i.e., 100yr-6hr) from datasets of NARCCAP and North American Regional Reanalysis (NARR) and accounted for projected changes in precipitation data using delta-change factors. Thakali et al. (2016) used data from four encompassing grids of the Flamingo and Tropicana watershed for the RFA. First, they aggregated 3-hour NARCCAP precipitation data to 6-hour precipitation data by shifting a 6-hour window through each 3-hour value. Using an algorithm, they calculated a series of 6-hour annual maximum data for each grid and model combination. For regionalization, they pooled the data by dividing each maximum by a median of the same data series for each grid. They fitted the generalized extreme value (GEV) distribution to each standardized pooled-annual extreme dataset of all four grids of each climate-model combination. The GEV distribution method is a commonly accepted approach in the nonstationarity study of extreme flows owing to the skewed nature of annual flow maxima and the ability to include covariates in the parameters of distribution (Thakali et al., 2016). Thakali et al. (2016) performed this process for all sets of data from each climate model. They then calculated the delta-change factors by dividing the projected future 100-year - 6-hour depth by historic 100-year - 6-hour depths.

Thakali et al. (2016) analyzed stormwater systems under the projected climate-change conditions using an existing Hydrologic Engineering Center's Hydrological Modeling System (HEC-HMS) model of the Las Vegas Valley watershed developed by the Clark County Regional Flood Control District (CCRFCD). The existing HEC-HMS model of the Flamingo and Tropicana watershed was used to assess the effects of climate change on stormwater facilities. The output from HEC-HMS was analyzed further according to guidelines from the CCRFCD design manual, and comparisons were made among the various climate projection scenarios.

Thakali et al. (2016) first performed a baseline HEC-HMS simulation where the existing HEC-HMS model was run with no changes. To assess the effects of climate change, they applied the delta change factor (DCF) calculated from the NARCCAP models to all existing design depths in the HEC-HMS model.

3.5. Discussion

This section provides a discussion of the approaches reviewed in terms of their original selection criteria as outlined in Section 3.2. It is worth noting that the success of any one approach over another is subject to local conditions, stakeholder influences, and dependent variables that are outside the scope of this research. **Figure 5** presents a summary overview of the approaches for accounting for climate change in the design of water infrastructure discussed in Sections 3.3 and 3.4. For each of the approaches, a qualitative score ranging from 1 to 4 for each of the four criteria with one being the least applicable for a given criteria and four being the most applicable for a given criteria, is proposed. These rankings are for discussion based on conclusions from the observations from the literature review and case studies.

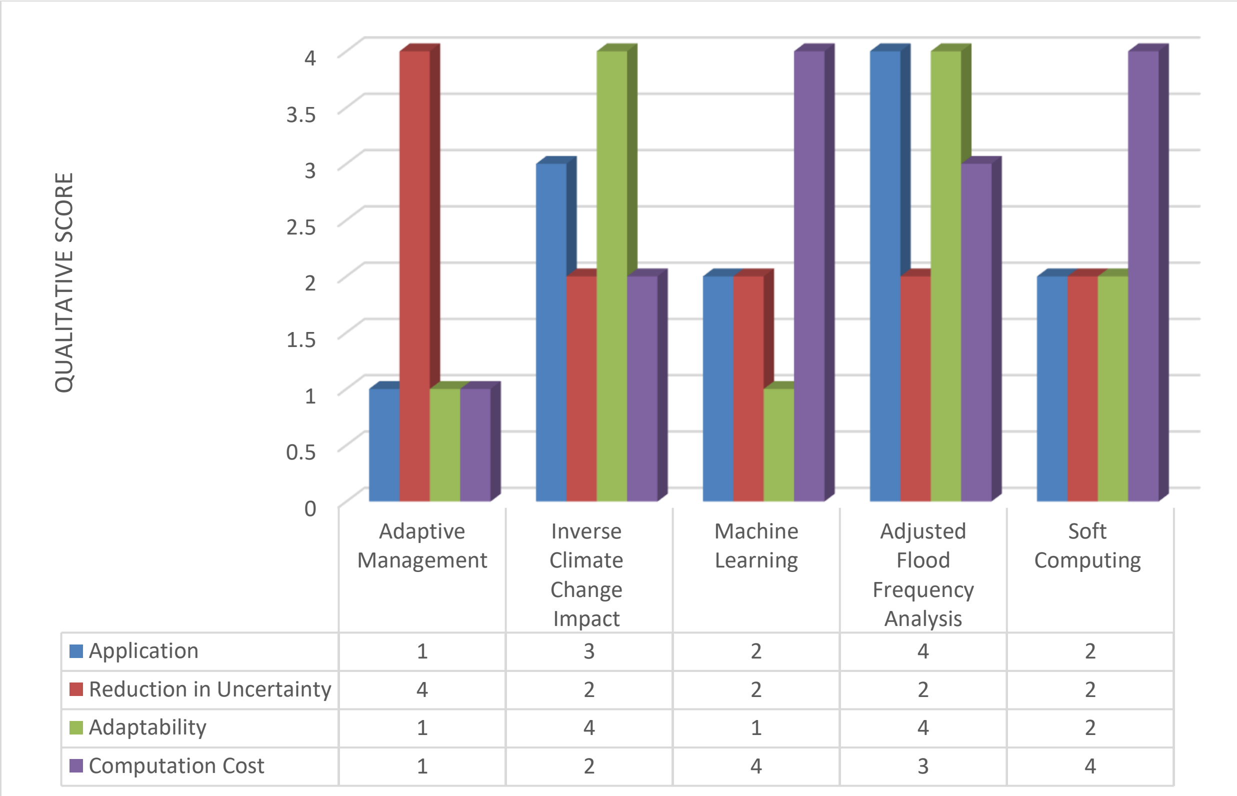


Figure 5: Qualitative Score of Reviewed Approaches

Based on the investigations in this study, adaptive management approaches are most likely to incorporate changes in climate data in future changes in design as they become available, with the disadvantage of requiring constant monitoring, management, and, in certain cases, changes to the built environment. Further, as noted by Allan et al. (2013), changing from conventional to adaptive approaches requires leadership and a reframing of the management perspective.

Inverse climate change impact approaches identify critical hydrological exposures that lead to system failures and determine the future climate change-informed conditions likely to result in the critical event. Inverse climate change impact approaches address the uncertainty in GCM projections by using the most conservative projections. As indicated in the discussed studies, Inverse climate change impact approaches are advantageous because they are scenario-independent (Guo et al., 2018), focus on specific existing and anticipated future water resource problems, have a direct link with the end-user, and allow for easy updating, when new and improved GCM outputs become available. Inverse climate change impact approaches are, however, narrow in their application since they only focus on one structure at a time.

Machine and deep learning techniques attempt to reduce the uncertainty with climate projections by reducing prediction errors in climate change forecasts and better quantifying the residual uncertainty. Machine learning approaches can numerically formulate flood nonlinearity solely based on historical data without requiring knowledge about the underlying physical processes. This is a major cost-saving attribute. However, the ability of machine learning and deep learning techniques to reduce uncertainty is often reliant on having an extensive amount of data to accurately train them. This is likely a major shortcoming of using machine learning approaches due to the lack of extensive historical climate change data within most basins. Machine learning and deep learning techniques may also not accurately account for future variations in climate due to their reliance on historical data.

The flood frequency and intensity duration curve approach attempts to reduce the uncertainty in climate projections and downscaling techniques by using an ensemble of climate change forecasts in the development of future flood frequency curves. As demonstrated by the reviewed case studies, these approaches are more widely accepted by water practitioners and have been extensively applied in basins across the United States (Stakhiv, 2011). Some of these approaches account for future changes in climate as an adjustment factor. This allows for future changes in the flood frequency curve once better data becomes available. It is worth noting that the resulting flood estimates from these approaches reflect the stationarity of the underlying data and distribution, and hence, the uncertainty of the resulting flood estimates could be higher in a rapidly changing climate.

Soft computing approaches, such as variations of extreme value theory that account for non-linearity due to climate change and fuzzy set theory, are mathematical programming formulations that predict future hydrological behavior based on probable future changes in precipitation extremes. As discussed in the literature review, soft computing approaches have been portrayed as having the capability to account for the uncertainties associated with future climate change projections. Since soft computing approaches are mathematical formulations, the preferences of hydrologists toward expected uncertain future changes in precipitation extremes can be included in the mathematical formulations. The inclusion of hydrologists' preferences toward expected uncertain future changes in precipitation extremes may lead to biases in the predictions.

In terms of applicability to water infrastructure design, the flood frequency analysis approach is likely the preferred option overall because it is most compatible with standard hydrological analysis methods. For this reason, the flood frequency analysis approach is widely accepted among water practitioners. Adaptive management approaches appear to be best suited for reductions in uncertainty. In terms of adaptability, both the flood frequency and the inverse climate change impact approaches appear to be viable approaches for water infrastructure design as they can be adapted to many basins. Machine learning and soft computing approaches are likely the least expensive to implement as they rely upon existing data, and the approaches and benefits of using sophisticated computational methods are ever-growing (Richards et al., 2023).

The approaches reviewed in this study are not inclusive of all studied approaches for addressing nonstationarity but rather those approaches that may provide an intermediate step for accounting for the inherent uncertainty in climate data that is used in designing and managing water infrastructure. Other approaches for addressing climate change include ecosystem modeling approaches (John A. et al., 2020), the Dynamic Adaptive Policy Pathways approach that utilizes simulation gaming to introduce uncertainty in decision makers' decision processes (Lawrence J. et al., 2017), weighted comprehensive assessment method (Xu, W. et al., 2022), and other more classical Bayesian methods for classifying uncertainty (Hobbs, 1997).

3.6. Recommended Approach for Accounting for Nonstationarity

Five approaches for accounting for climate change in the design of water infrastructure are presented in this dissertation: adaptive management, inverse climate change impact method, machine learning, updated flood frequency analysis, and soft computing approaches. Except for the soft-computing approaches, all these methods rely on climate projections from GCMs and downscaling techniques. All five approaches recognize that there is uncertainty in climate data available for decision-making due to the uncertainty in the GCM outputs and the downscaling methods, among others.

The flood frequency analysis approach may likely be the most applicable to water infrastructure design as it may be, among those reviewed, the least disruptive in terms of standard hydrological analysis methods, likely cost-effective, and is likely adaptable to most basins. However, adaptive management approaches may be best suited for reductions in uncertainty since they provide opportunities to constantly adjust decisions based on improved climate change data. A combination of flood frequency and adaptive management approaches is therefore recommended as an effective and practical way of accounting for climate change in the design and management of water infrastructure.

CHAPTER 4: ADAPTIVE MANAGEMENT FRAMEWORK

In Chapter 1, the need to develop a demonstrably improved approach for designing and managing water infrastructure that uses quantifiable hydrological estimates of the future climate and accounts for multiple objectives from multiple stakeholders was presented. This need stems from the fact that, (1) although the climate is changing (IPCC,2014), traditional approaches to the hydrologic design of water infrastructure typically assume that the climate is stationary and that historic data reflect future conditions and (2) water infrastructure design and management is usually considered a single-objective problem without accounting for the inter-connections between the primary design objective and other basin objectives. The single-objective approach is unable to deal adequately with the challenges of complex systems such as multi-use river basins that require an understanding of the linkages between the various uses and stakeholders (Anderson, et al., 2008).

In Chapter 3, it was established that a combination of the flood frequency and adaptive management approaches could provide an improved way of accounting for climate change in the design of water infrastructure. This is because the flood frequency analysis approach was found to be most applicable to water infrastructure design as it is, among those reviewed, the least disruptive in terms of standard hydrological analysis methods, is cost-effective, and adaptable to most basins. However, adaptive management approaches may be best suited for reducing uncertainty overall since they provide for opportunities to continually adjust decisions based on improved climate change data.

Building on work done in Chapters 1 and 3, this chapter summarizes findings from semi-structured interviews and presents the development of the adaptive management elements of the hybrid framework that allows for future updates based on increased forecast accuracy and allows for accounting for other basin objectives in addition to the primary basin objective. This chapter answers Research Questions 2 and 3(b), which are restated here:

Research Question 2 – What are the approaches for accounting for multi-use basin objectives in the design and management of water infrastructure?

Research Question 3(b) – What is the most effective and practical approach for accounting for multiple competing objectives from multiple basin uses?

The findings from the semi-structured interviews, and the development of the adaptive management framework are described in the subsections below.

4.1. Semi-Structured Interviews

Semi-structured interviews with water practitioners provided foundational understanding of multi-use basin objectives. The purpose of the interviews was to help answer questions related to designing for, and managing multiple basin objectives such as:

1. *What are the approaches for accounting for multi-use basin objectives in the design and management of water infrastructure?*
2. *How can the multiple basin objectives and nonstationarity be accounted for in the design and management of water infrastructure?*
3. *What are the sources of uncertainty and how can they be mitigated?*

The goal of the semi-structured interviews was to solicit ideas about how analytical methods and adaptive management practices have been implemented in the past and how they can be implemented in multi-objective basins to account for uncertainty in climate projections and socio-physical changes such as basin objectives and land use changes.

Results from the interviews highlight the challenge in optimizing a design for multiple objectives mainly because of the subjectivity involved with assigning weights or importance to various basin objectives. Each basin stakeholder is likely to view their objective as the most important objective. This research, therefore, pivots to an adaptive management framework that defines and maintains objectives of existing basin users for a period (baseline conditions) while designing the primary water infrastructure in a manner that accounts for nonstationarity and uncertainty. With this approach, the primary basin objective is optimized while all other basin objectives are considered on a pass/fail basis. Unlike other approaches such as Monte Carlo or weighted multi-criteria decision analysis, this approach is cost effective and has limited subjective components.

Conrad et al. (2013) define adaptive management for the water industry as an iterative process for improving and revisiting management policies and practices by learning through monitoring and from outcomes of rigorously designed investigations. The generalized sequence in adaptive management involves analysis of the problem that needs to be solved, developing a design and or management plan, implementing the plan, monitoring, and evaluating. The evaluation results are then fed back into the decision-making process to aid future planning and management. Adaptive management can provide the framework to develop fundamental decision-making processes for adaptation in the context of uncertainty and evolving engineering and planning paradigms to increase flexibility (Conrad et al., 2013).

4.2. Adaptive Management Framework

A pilot multi-use basin (Buckhorn Creek Basin) was explored to develop an adaptive management framework that allows for future updates to design, and management based on increased forecast accuracy and changes in basin objectives. The adaptive management framework is shown in the flowchart in **Figure 6.**

As noted in the previous section, optimizing a design for multiple objectives will prove challenging mainly because of the subjectivity involved with assigning weights or importance to various basin objectives. The framework, therefore, aims to define and maintain (for a period) baseline objectives of existing basin users while designing the primary water infrastructure in a manner that accounts for nonstationarity and uncertainty. A combination of design updates based on results from an H&H model and a management plan is used to account for nonstationarity and uncertainty. The baseline conditions are reviewed regularly, at which time they are redefined. If there are no changes in the initial baseline conditions, the current management plan is maintained. However, if there are changes in the baseline conditions, the H&H model is updated with the revised baseline conditions and simulated for updated design flood levels. The updated design flood levels are then incorporated into an updated management plan. This cycle is repeated till the tenth year after design, at which point changes to the built infrastructure are recommended.

The result of performing these steps provides a demonstrably improved approach for designing and managing water infrastructure that uses quantifiable hydrological estimates of the future climate and accounts for multiple objectives from multiple stakeholders. The framework requires a review and baseline objectives update timeframe. A two-year review cycle was selected.

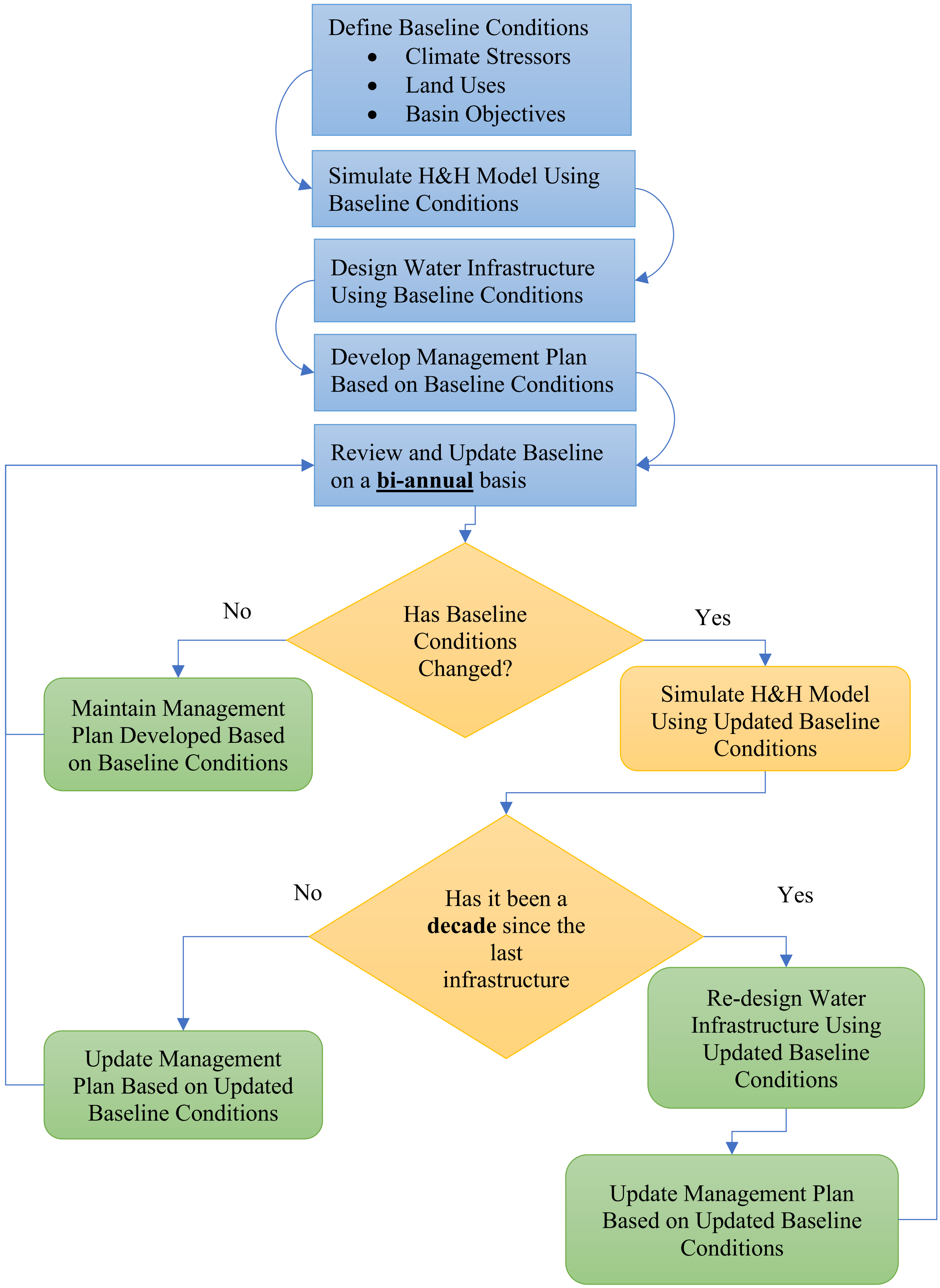


Figure 6: Adaptive Management Framework

4.3. Designing an Adaptive Management Framework using the Buckhorn Creek Basin

The adaptive management framework shown in **Figure 6** has two main components:

1. Develop an approach for hydrologic and hydraulic design with climate forecast to address the issue of nonstationarity and account for multiple objectives.

2. Managing uncertainty. There is uncertainty in the inputs needed for hydrologic and hydraulic design, such as land use changes due to urbanization and in the climate forecast data. Additionally, basin objectives could be a source of uncertainty as objectives may change with time either due to changes in basin uses or human interests. The adaptive management framework needs to be flexible and able to respond as situations change (Conrad et al., 2013).

4.3.1. Designing for nonstationarity and multiple objectives

4.3.1.1. Accounting for multiple objectives

Accounting for various objectives within multi-use basins requires the identification of the basin uses and objectives. The research focused on the Buckhorn Creek Basin. The basin area is about 231 square miles, spanning across the counties of Wake, Chatham, Lee, and Harnett counties in North Carolina (See Figure 7). The Cape Fear River flows through the basin. Multiple tributaries to the Cape Fear River originate from the basin. These tributaries include Wombles Creek, Gulf Creek, Little Shaddox Creek, Lick Creek, Bush Creek, Falls Creek, Daniels Creek, Cedar Creek, Camels Creek, Parkers Creek, and Avents Creek. Other streams within the basin include Buckhorn Creek, Horse Branch, Jim Branch, Norris Branch, Utley Creek, Little Creek, White Oak Creek, Little White Oak Creek, Big Branch, Thomas Creek, and Tom Jack Creek.

The Buckhorn Creek basin is home to the Buckhorn Dam, the Shearon Harris Nuclear Power Plant, the Shearon Harris County Park, the Shearon Harris Reservoir, the City of Sanford, NC water plant and Duke Energy facilities (See **Figure 7**).

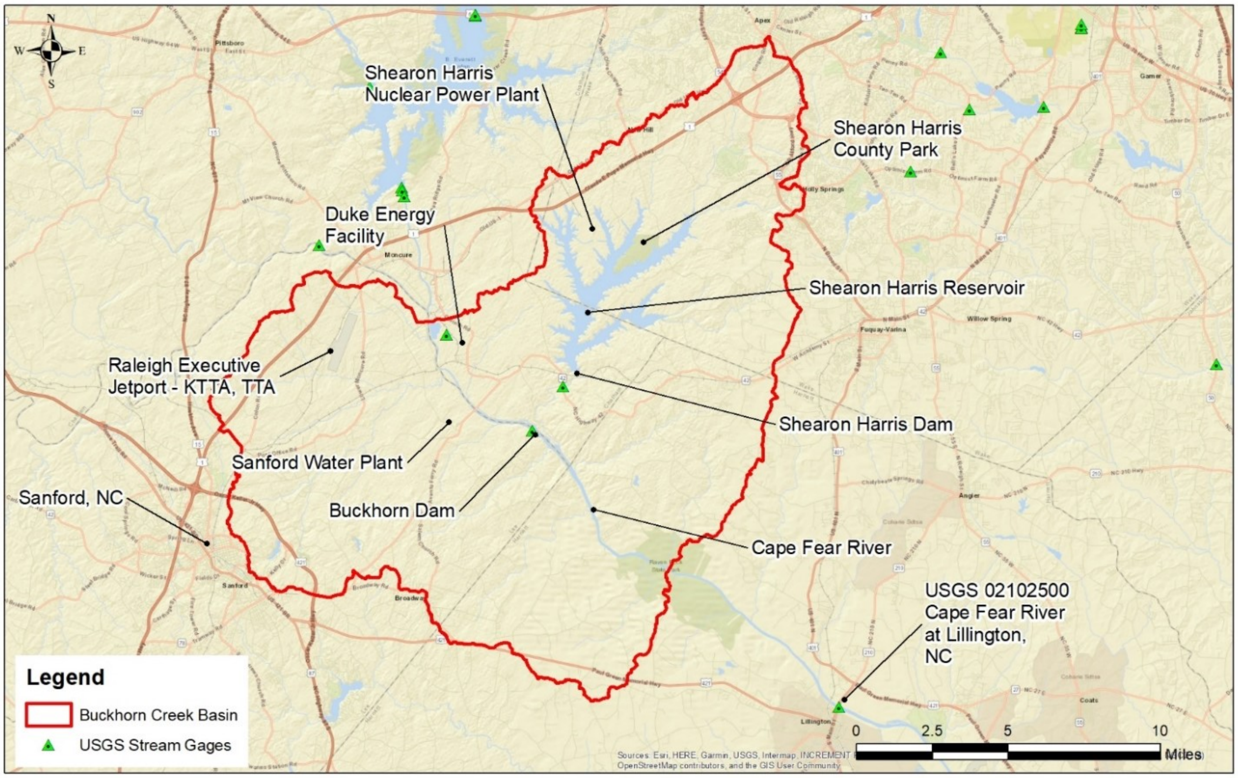


Figure 7: Buckhorn Creek Basin

Basin Uses

The Buckhorn Creek is used for:

1. Recreation: The basin has natural features such as reservoirs that are used for recreational purposes such as fishing, boating, and outdoor recreation. The basin is home to the Shearon Harris County Park and the Shearon Harris Reservoir among others.

2. Power Generation: The Shearon Harris Nuclear Power Plant is located within the basin near the Shearon Harris Reservoir. The nuclear power plant uses the water from the reservoir for cooling. The nuclear power plant is operated by Duke Energy and generates about

900 MWe of electricity as part of the electricity supply for the state of North Carolina.

3. Water Supply: The Buckhorn Lake Dam (NC STATEID: CHATH-022) is a dam along the Cape Fear River (within Chatham County) that was originally designed to impound water for hydropower generation. The dam was constructed in 1915 and is owned by Carolina Power and Light (now Duke Energy). The hydroelectric plant at the dam was decommissioned in 1963 although the dam remains. The nearby town of Sanford uses the impoundment for water supply and has an intake within the reservoir.

Basin Objectives

These basin uses inform the basin objectives. As part of my research, semi-structured interviews with the various stakeholders within the basin were performed to collect data on the basin objectives. The baseline basin objectives will be to maintain the current uses:

- Recreation: Maintain the recreational uses of the basin. This requires identifying and quantifying recreational uses, so it is measurable.
- Power Generation: Maintain the power generation uses of the basin. This requires identifying and quantifying power generation uses, so it is measurable.
- Water Supply: Optimize water supply withdrawals from the impoundment created by the Buckhorn Dam without impacting the recreational and power generation uses of the basin.

The Cape Fear River is a heavily regulated river. One of the regulatory requirements is to maintain environmental flows at the USGS gauge downstream of Raven Rock State Park of 550 cfs plus or minus 50 cfs. This requirement will have to be met under current and future climate conditions.

4.3.1.2. Designing for nonstationarity

The developed framework combines the updated flood frequency and adaptive management approaches from Conrad et al. (2013) to present a means to account for climate change in the design of water infrastructure. The framework assumes that a hydrologic and hydraulic (H&H) model will be developed for the express purpose of designing the primary objective of the water infrastructure and the updated flood frequency analysis approach will be used in determining the precipitation boundary condition to the H&H model. Precipitation forecasts from Global Circulation Models (GCMs) will be used in developing the precipitation boundary condition.

4.3.2. Managing Uncertainty

4.3.2.1. Sources of Uncertainty

To manage uncertainty, the sources of uncertainty in the design and management of water infrastructure in multi-use basins must first be identified. Semi-structured interviews were performed in the process of identifying the sources of uncertainty. The identified sources of uncertainty are:

1. *Climate forecast*: estimates of future climate are usually made using GCMs. GCMs use carbon emission forecasts, that are highly uncertain, as input. Additionally, the prediction accuracy of GCMs is not refined enough to capture the climate at the local (design-based) level. Regional scale GCM outputs are therefore downscaled to local scales using predetermined relationships between GCM outputs and the regional climate data. This technique, however, inaccurately assumes that the relationship between the GCM outputs and the regional climate data derived based on historical data is valid for future data. This

assumption is referred to as statistical stationarity (Dixon et al., 2016). Climate forecasts, even in their best state, have a high level of uncertainty.

2. *Urbanization and other developments within the basin*: Local scale data related to land uses are important because they are used in establishing downscaling information for climate projections and because they are directly correlated to the transformation of precipitation into streamflow and flood elevations. Changes in land use may be predicted with some degree of accuracy using zoning plans, but the actual timing of how the changes will occur is always guesswork. Temperature and precipitation change due to climate change could also alter landforms drastically. Land use change is, therefore, another major source of uncertainty.
3. *Basin objectives*: As previously discussed, basin objectives do and will change when basin uses change. Although some changes in basin objectives may be determined by human decisions, basin uses and their corresponding objectives, may be necessitated by unforeseen basin transformations due to climate change.

4.3.2.2. Baseline Conditions

The proposed second step in managing uncertainty is to define baseline conditions for the identified sources of uncertainty. This approach uses an uncertainty analysis as in the effect of changes to baseline conditions. This requires the identification of baseline conditions. Baseline conditions will be determined by soliciting data from stakeholders within the pilot project basin.

4.3.2.3. Management Plan

An adaptive management approach allows for future changes in design as more accurate climate data becomes available but has the downside of requiring constant monitoring, management, and, in certain cases, changes to the built environment, which may be undesirable. An acceptable framework is one that minimizes changes to the built environment. This framework, therefore, proposes to manage changes in the sources of uncertainty by managing their impacts until a duration/time when the change from the baseline condition is large enough to make it cost-effective to alter the design of the built infrastructure. Timescales are discussed in the next section.

4.3.2.4. Review and Monitoring Timescales

The proposed framework starts with (1) defining baseline conditions, (2) simulating an H&H model using the baseline conditions including climate forecast data, (3) designing a water infrastructure using the results of the H&H model simulation, and (4) developing a management plan based on the baseline conditions.

The framework requires a review and update of the baseline conditions on a bi-annual basis. A two-year review cycle was selected because changes in baseline conditions, either due to improvement in prediction or human decisions (including changes in stakeholders and their preferences), are likely to be noticeable at this stage. If there are no changes in the initial baseline conditions, the current management plan is maintained. However, if there are changes in the baseline conditions, the H&H model is updated with the revised baseline conditions and simulated for updated design flood levels. The updated design flood levels are then incorporated into an updated management plan. This cycle is repeated till the tenth year after design, at which point changes to the built infrastructure are recommended. A 10-year cycle was chosen for updating the built design for the following reasons:

1. It is long enough to have a level of certainty in changes in the climate data. The United States Geological Survey (USGS), in Bulletin 17B/C, recommends a 10-year minimum record length for statistical analysis for this reason (England et al., 2019).

2. Other federal agencies, such as the Federal Emergency Management Agency (FEMA), use the 5-year cycle for updating floodplain management regulations, so it is likely that federal standards about water infrastructure design may be different after two cycles of updates.

In lieu of a 10-year cycle, changes to the built environment could be timed to other rigid constraints such as bond timelines, regulatory timelines, or even political timelines. It is worth noting that changes to the built environment could be limited or may not be possible if there are constraints in place that affect the levels of changes that can be made.

4.4. Adaptive Management Framework within the Systems Engineering Context for the Pilot Basin

The classic Systems Engineering V-diagram has two sides. The left side relates to the definition and decomposition of the systems engineering problem, and the right side relates to Integration and Testing. Connecting the left and right sides of the V-diagram are several verification plans that enable the verification of the system at the component, sub-system, and system levels and assess if the entire system is validated (see **Figure 8**; Kossiakoff, A. et al., 2011). A system is considered validated if the integrated system performs as intended (i.e., solves the identified problem for which the system was designed).

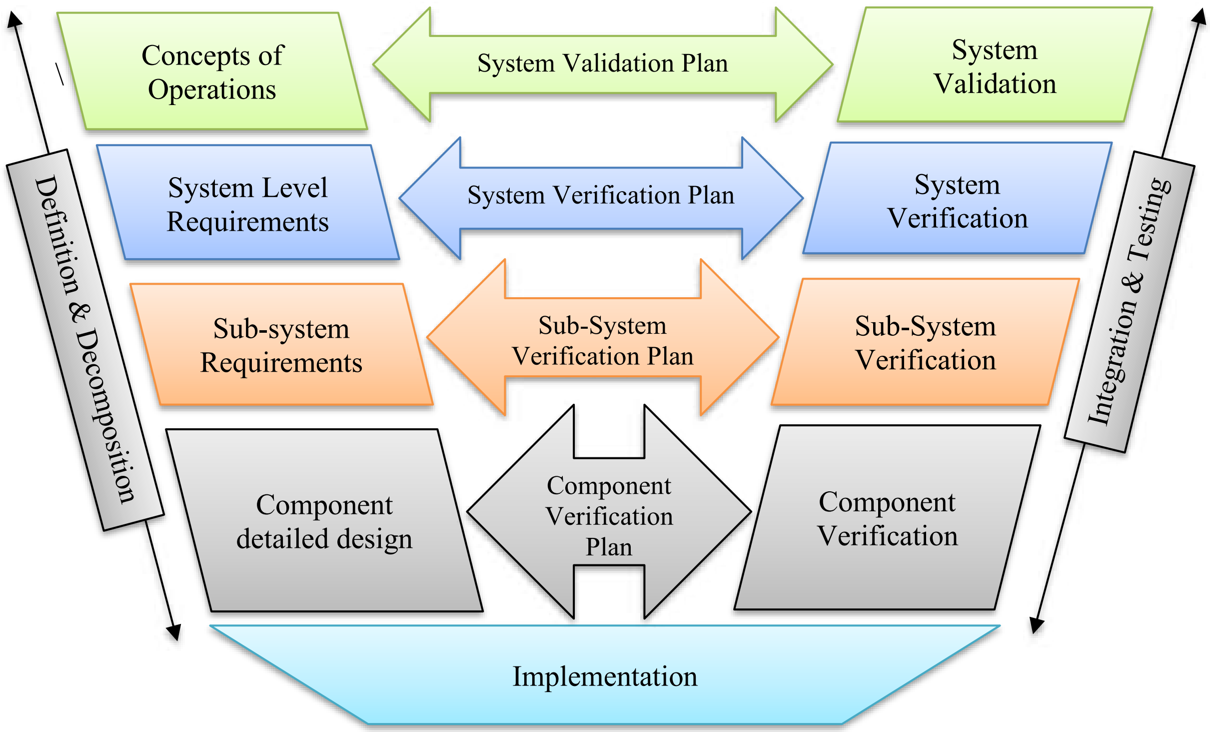


Figure 8: Systems Engineering V- Diagram (Kossiakoff, A. et.al., 2011)

The adaptive management framework for the pilot basin can be described in terms of the classic systems engineering V-diagram as follows:

4.4.1. Definition and Decomposition

4.4.1.1. System Level Requirements

There are multiple basin uses within the Buckhorn Creek (pilot) basin. However, the basin use/objective chosen to demonstrate the application of the adaptive management framework is water supply for the city of Sanford, NC. The water infrastructure for the water supply use is the Buckhorn Dam and the reservoir it impounds. The location of the Buckhorn Dam, the City of Sanford water treatment plant, and the other water infrastructure within the basin are shown in **Figure 9**.

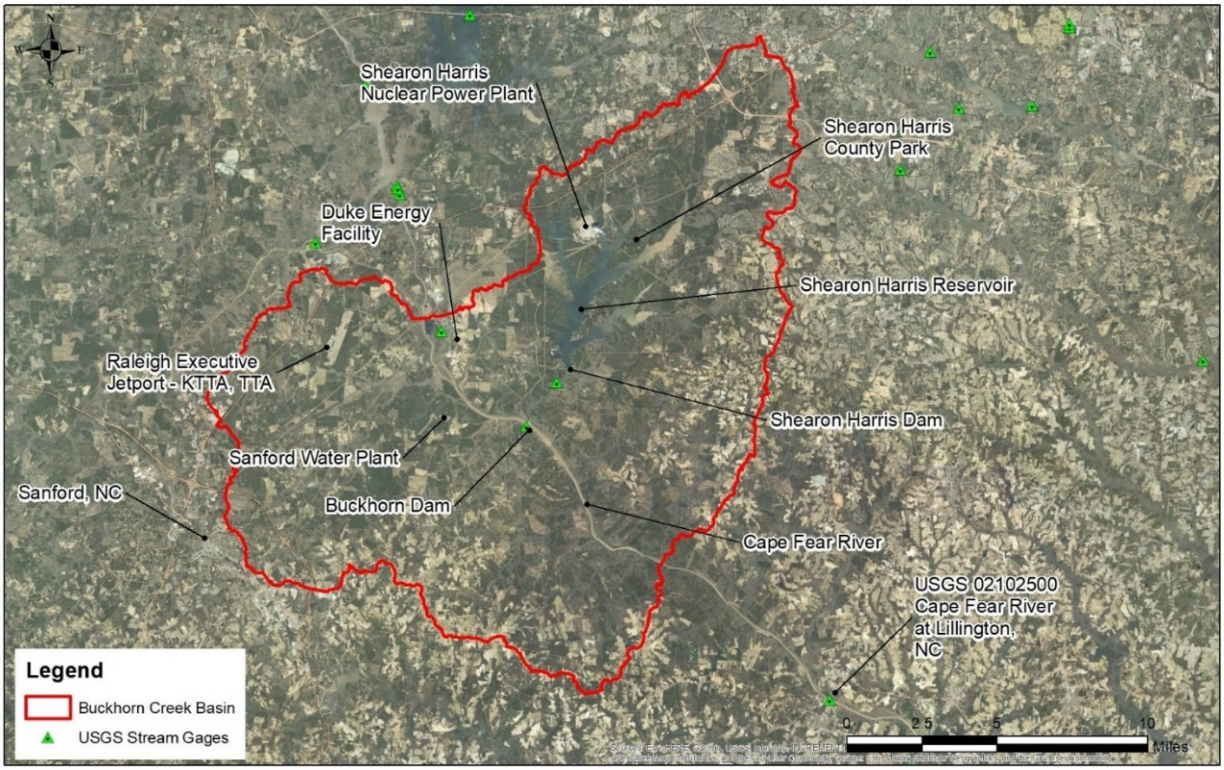


Figure 9: Buckhorn Creek Basin Uses

The system-level requirement for the pilot basin is outlined as follows:

Optimize the City of Sanford, NC, water supply withdrawals from the impoundment created by the Buckhorn Dam under present and future conditions without impacting the recreational and power generation uses of the basin.

4.4.1.2. Sub-system Level Requirements

The adaptive management framework has two main components:

1. Develop an approach for hydrologic and hydraulic design with climate forecast to address the issue of nonstationarity and account for multiple objectives.

2. Managing uncertainty in climate and changes in basin objectives.

The climate and uncertainty elements are the two main sub-systems of the adaptive management framework. The sub-system level requirements can be defined as:

- *Water infrastructure within the basin should be hydrologically functional under present and future climatic conditions.*
- *Water infrastructure within the basin should meet the objectives of current and future basin uses.*
- *Maintain minimum flow requirements at the USGS gauge downstream of Raven Rock State Park of 550 cfs plus or minus 50 cfs.*

4.4.1.3. Component Level Requirements

The components are climate (and forecast) and the sources of uncertainty including land use changes and changes in the various basin objectives. Projected population growth for the City of Sanford, NC is also a source of uncertainty since that will determine the water supply demands.

The component level requirements can be defined as:

- *Buckhorn Dam and the water it impounds should be adequate to meet the water supply needs of the City of Sanford, NC even under a changing climate.*
- *Water levels in the Shearon Harris Reservoir should remain within the elevation ranges needed to cool the Shearon Harris Nuclear Power Plant under current and future climate conditions.*
- *Water levels in the Shearon Harris Reservoir should remain within the elevation ranges needed for boating, fishing, and other recreational uses under current and future climate conditions.*
- *Minimum environmental flows within the Cape Fear River at the location of the USGS gauge downstream of Raven Rock State Park should be 550 cfs plus or minus 50 cfs.*

4.4.2. Integration and Testing

4.4.2.1. Component Verification

The component level requirements specify that the various system components (Shearon Harris Reservoir, Buckhorn Dam, and Cape Fear River operate within ranges that enable the basin objectives to be met. The operating ranges for the various components, therefore, need to be defined so that they can be measured and assessed. The desired operating ranges are subject to change with changing basin objectives. The operating ranges over a given period are defined as baseline conditions.

The component verification will entail the following:

1. *Definition of baseline conditions, and*
2. *Review and updating of the baseline conditions every other year.*

Defining baseline conditions as part of the adaptive management framework is an integral part of this research, as shown in the linear research framework (See **Figure 10**).

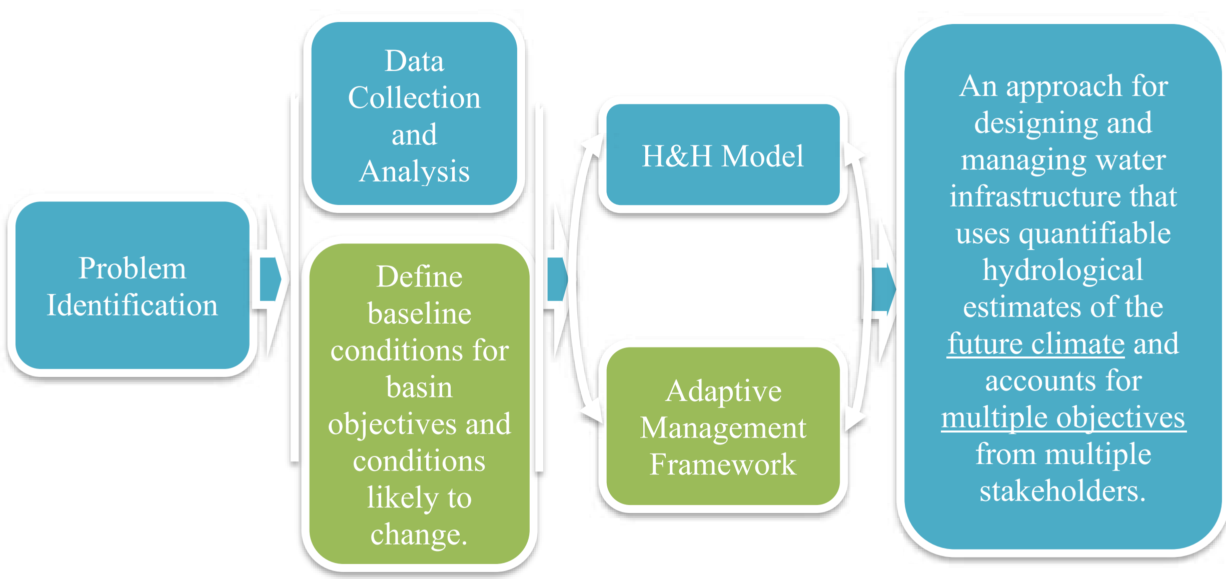


Figure 10: Baseline Conditions and Linear Framework for Research

The baseline conditions for the pilot basin are defined in **Chapter 6**.

4.4.2.2. Sub-system Verification

The sub-system level requirements specify that water infrastructure within the basin should be hydrologically functional under present and future climatic conditions and should meet the objectives of current and future basin uses, while also meeting the environmental constraint of maintaining a minimum flow requirement of 550 cfs plus or minus 50 cfs within the Cape Fear River.

The sub-system verification will entail the following:

1. *Simulating the H&H model using the baseline conditions to ensure that the sub-system requirements are being met, and*
2. *Updating the baseline conditions within the H&H model bi-annually and re-simulating the model to ensure that the sub-system requirements continue to be met.*
3. *Develop and update a management plan that mitigates against stresses on sub-system performance due to changes in climate and hydrological design inputs such as land use and basin objectives.*

4.4.2.3. System Verification and Validation

The system level requirements specify that the primary basin use of water supply is optimized by optimizing the city of Sanford, NC water supply withdrawals from the impoundment created by the Buckhorn Dam, under present and future conditions, without impacting the recreational and power generation uses of the basin.

System verification and validation will entail the following:

1. *Development of key performance indicators (KPIs) that can be used as basis for assessing performance of the system.*

2. *Comparison of the performance, using the KPIs developed under (1), of the system developed under this research framework to one developed under the current state of practice (single-objective design with expected climate impacts at the end of design life accounted for).*

The implementation, verification, and validation of the adaptive management framework for the Buckhorn Creek Basin (pilot basin) is described in **Chapter 6**.

CHAPTER 5: HYDROLOGIC AND HYDRAULIC DATA AND MODEL DEVELOPMENT

In Chapter 3, a hybrid approach for addressing the issue of nonstationarity was developed. In Chapter 4, the adaptive management framework was detailed as well as how the framework would address the issue of multiple objectives from multiple basin uses. This chapter and subsequent chapters demonstrate how these elements combine for a unified approach for designing and managing water infrastructure that uses quantifiable hydrological estimates of the future climate and accounts for multiple objectives from multiple stakeholders in the Buckhorn Creek Basin.

This chapter specifically contributes to research Question 3, which is restated below, by discussing the development of precipitation data that accounts for a changing climate and the development of hydrologic and hydraulic model that can be used to transform the precipitation data into flow rate and stage data for water infrastructure design.

Research Question 3 – How can the issues of nonstationarity and multiple basin objectives be addressed?

Figure 11 shows how the development of the climate-informed precipitation data and hydrologic and hydraulic models fit into the general hybrid framework for designing and managing water infrastructure in multi-use basins.

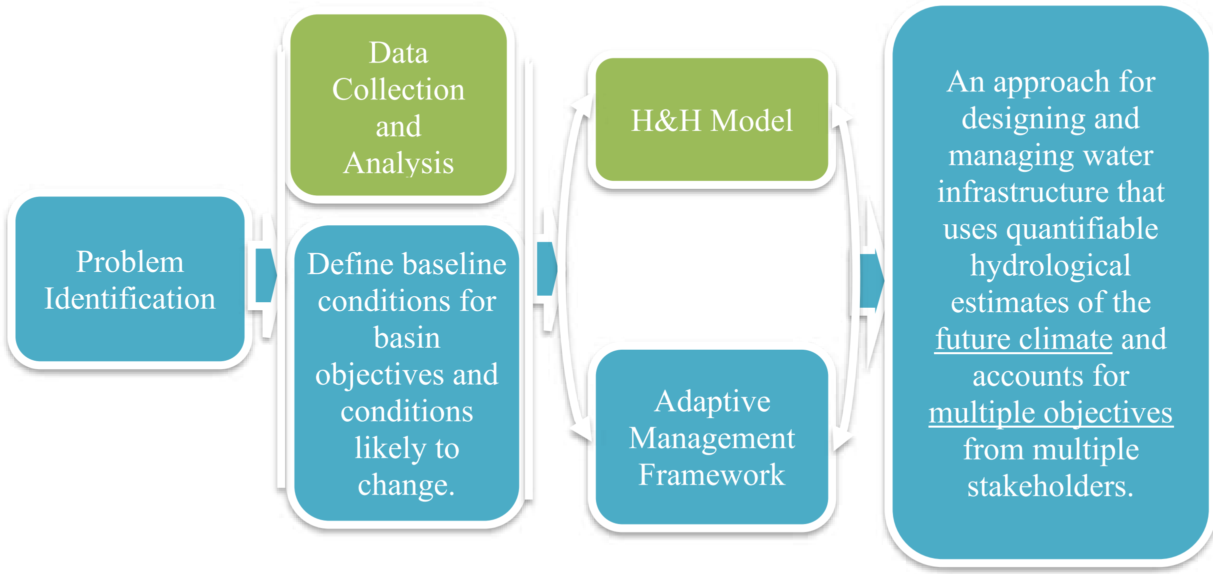


Figure 11: Climate Data, H&H model, and Linear Framework for Research

5.1. Pilot Basin

5.1.1. Key Infrastructure

The Buckhorn Creek basin characteristics and uses are described in Chapter 4. Buckhorn Creek basin is a subbasin within the Cape Fear River Basin (see **Figure 12**). The key water infrastructure within the basin that is accounted for in design includes:

The Shearon Harris Lake: The Shearon Harris Lake is one of the largest reservoirs by surface area within the Cape Fear Basin. The lake is impounded by the Shearon Harris Dam and has a surface area of 4,100 acres. Although the reservoir may provide some flood attenuation, flood control is not its primary purpose. The lake is operated by Duke Energy as a source of cooling water for the Shearon Harris Nuclear Power Plant. The lake discharges into Buckhorn Creek, which is a tributary of the Cape Fear River.

Buckhorn Dam**:** Buckhorn Dam is located on the Cape Fear River, just upstream of the confluence between the Cape Fear River and Buckhorn Creek. The dam is a run-of-the-river dam and was originally constructed to generate hydropower. The impoundment behind the dam is currently used as a drinking water source for the Town of Sanford, NC.

***B. Everett Jordan Lake (Jordan Lake)*:** Jordan Lake is located immediately north of the Shearon Harris Reservoir and is the main flood control feature within the entire Cape Fear River Basin. Jordan Lake was constructed between 1973 and 1983 along the Haw and New Hope Rivers by the U.S. Army Corps of Engineers (USACE) as a flood mitigation feature after the major flooding from the tropical storm in September of 1945. The surface area of Jordan Lake is 13,940 acres. Although the primary purpose of the reservoir is flood control, it also functions as a major water supply facility, providing water to communities in Chatham, Orange, and Wake Counties. Jordan Lake is not located within the Buckhorn Creek basin but contributes flows into the Cape Fear to meet the minimum environmental flow requirement.

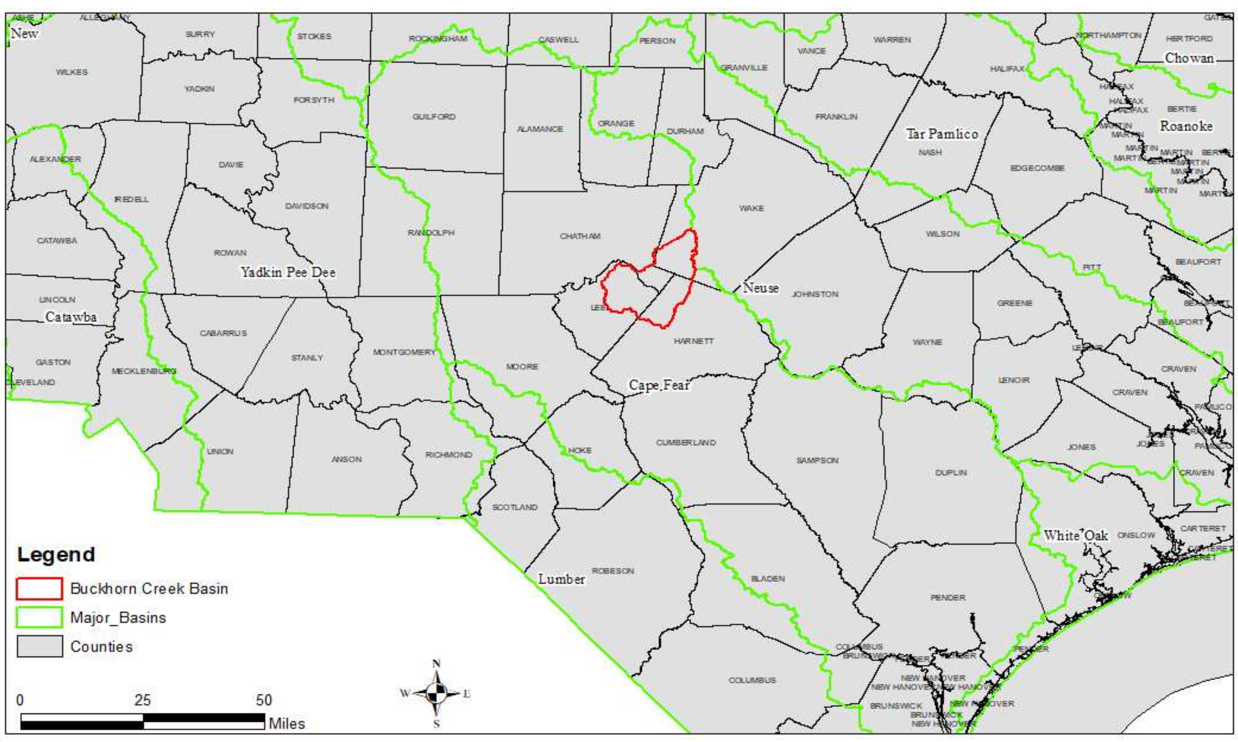


Figure 12: Cape Fear River Basin

5.1.2. Land Cover Trends

National Land Cover Dataset (NLCD) compiled by the Multi-Resolution Land Characteristics Consortium (USGS, 2023), is available for Buckhorn Creek for 2001, 2006, 2011, 2016, and 2019. The land cover types within the basin are listed in **Table 2**.

Table 2: NLCD Land Cover Classes

Class \ Value		**Classification Description**	**Class \ Value**		**Classification Description**
Water	11	Open Water	**Shrubland**	51	Dwarf Scrub
	12	Perennial Ice/Snow		52	Shrub/Scrub
Developed	21	Developed, Open Space	**Herbaceous**	71	Grassland/Herbaceous
	22	Developed, Low Intensity		72	Sedge/Herbaceous
	23	Developed, Medium Intensity		73	Lichens
	24	Developed High Intensity		74	Moss
Barren	31	Barren Land (Rock/Sand/Clay)	**Planted / Cultivated**	81	Pasture/Hay
Forest	41	Deciduous Forest		82	Cultivated Crops
	42	Evergreen Forest	**Wetlands**	90	Woody Wetlands
	43	Mixed Forest		95	Emergent Herbaceous Wetlands

The percentages of the various land cover types within the basin from 2001, 2006, 2011, 2016, and 2019 are shown in **Table 3**. As shown in **Table 3**, the percentage of the basin that was developed increased gradually from 2001 to 2019. The increase in developed areas coincides with reductions in the deciduous forest land cover types. The 2019 land cover types were used as the baseline condition for the Buckhorn Creek basin.

Table 3: Land Cover Trends in the Buckhorn Creek Basin

Landcover Type	Year				
	2001	**2006**	**2011**	**2016**	**2019**
Open Water	4%	4%	4%	4%	4%
Developed, Open Space	**4%**	**5%**	**5%**	**5%**	**5%**
Developed, Low Intensity	**2%**	**2%**	**2%**	**3%**	**3%**
Developed, Medium Intensity	1%	1%	1%	1%	1%
Developed, High Intensity	0%	0%	0%	0%	0%
Barren Land	0%	0%	0%	0%	0%
Deciduous Forest	**17%**	**16%**	**14%**	**12%**	**12%**
Evergreen Forest	27%	28%	29%	30%	31%
Mixed Forest	20%	20%	20%	20%	19%
Shrub/Scrub	2%	2%	3%	5%	5%
Herbaceous	7%	7%	7%	6%	5%
Hay/Pasture	7%	6%	6%	6%	6%
Cultivated Crops	5%	5%	5%	5%	5%
Woody Wetlands	4%	4%	3%	4%	4%
Emergent Herbaceous Wetlands	0%	0%	0%	0%	0%
Total	**100%**	**100%**	**100%**	**100%**	**100%**

5.1.3. Rainfall and Streamflow Data

5.1.3.1. Rainfall Data

The average annual rainfall in the Buckhorn Creek Basin is about 47 inches. This estimate is based on data collected by the PRISM Climate Group from 1980 and 2010 (NACSE, 2023). Point precipitation estimates for various return periods for locations within the Buckhorn Creek Basin can be obtained from the National Ocean and Atmospheric Administration (NOAA) Atlas 14 Volume 2 or digitally from NOAA's Precipitation Frequency Data Server at https://hdsc.nws.noaa.gov/hdsc/pfds/. **Table 4** lists rainfall depth frequencies for the 6-, 12-, and 24-hour periods within the basin. The coordinates used are Latitude: 35.5505° and Longitude: -78.9854°.

Table 4: NOAA Atlas 14 Precipitation Frequency Depth Estimates

Duration (hrs)	**Average Recurrence Interval (Depths in Inches)**						
	2-Yr	**10-Yr**	**25-Yr**	**50-Yr**	**100-Yr**	**500-Yr**	**1000-Yr**
6	2.58	3.75	4.46	5.06	5.66	7.18	7.91
12	3.05	4.48	5.38	6.13	6.91	8.92	9.91
24	3.58	5.23	6.22	7.01	7.82	9.82	10.70

The National Weather Service (NWS) operates a network of rainfall gauges across North Carolina, the majority of which are part of the Cooperative Observer Program (COOP) network. COOP network gauges in North Carolina have some of the longest periods of rainfall records in the state, including several with records that are more than 100 years old. The State Climate Office of North Carolina (SCO) compiles and archives records from more than 37,000 North Carolina weather sites, including those in the COOP network, in the North Carolina Climate Retrieval and Observations Network of the Southeast (CRONOS) Database. The SCO compiled monthly rainfall records from the three closest gauges to the Buckhorn Creek Basin are shown in **Table 5**. **Table 5** shows the gauge name, identifying number, period of record, and other characteristics of these rainfall gauges. The locations of these rainfall gauges are shown in **Figure 13**.

Table 5: Long-Term Rain Gauges near Buckhorn Creek Basin

Rainfall Gauge Location and Number	County	Period of Record	Latitude	Longitude	Elevation
Fayetteville PWC (313017)	Cumberland	1871 - 2021	35.0583	-78.8583	96
Dunn 4 NW (312500)	Harnett	1962 - 2021	35.3247	-78.6881	200
Carthage WTP (311515)	Moore	1948 - 2021	35.3319	-79.4067	440

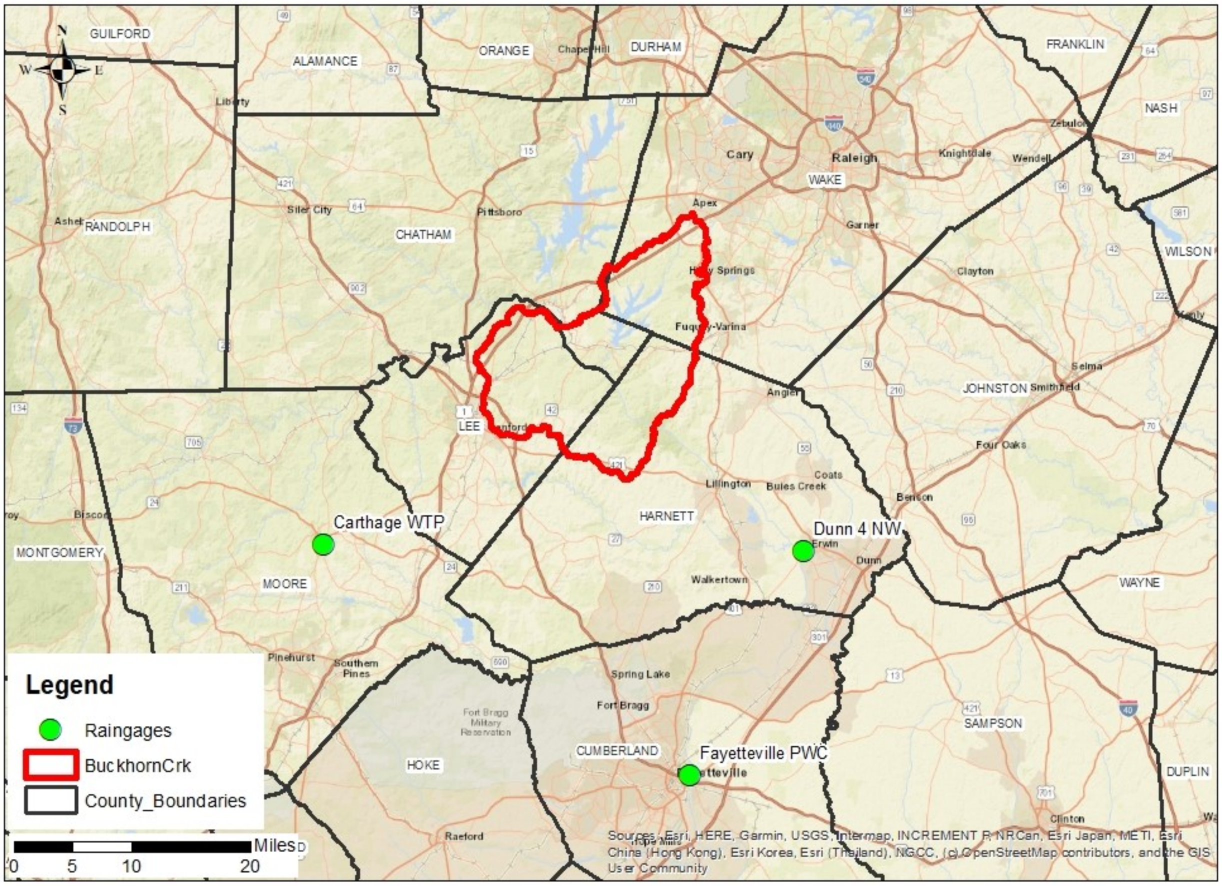


Figure 13:Location of Long-Term Rain Gauges around the Buckhorn Creek Basin Study Area

5.1.3.2. Stream Gauge Data

The USGS currently maintains 49 active stream gauges within the Cape Fear Basin. Within the Buckhorn Creek basin, there are USGS stream gauges on the Cape Fear River and one immediately downstream of the Shearon Harris Dam (USGS gauge 02102192 – Buckhorn Creek NR Corinth, NC) within the Buckhorn Creek Basin. Measurements at USGS gauge 02102178 (Cape Fear R at Buckhorn Dam) were discontinued in 2010).

Environmental flows within the Cape Fear Basin are monitored at USGS gauge 02102500 (Cape Fear River at Lillington, NC), which is located downstream of the basin. The USGS stream gauge locations are shown in **Figure 14**.

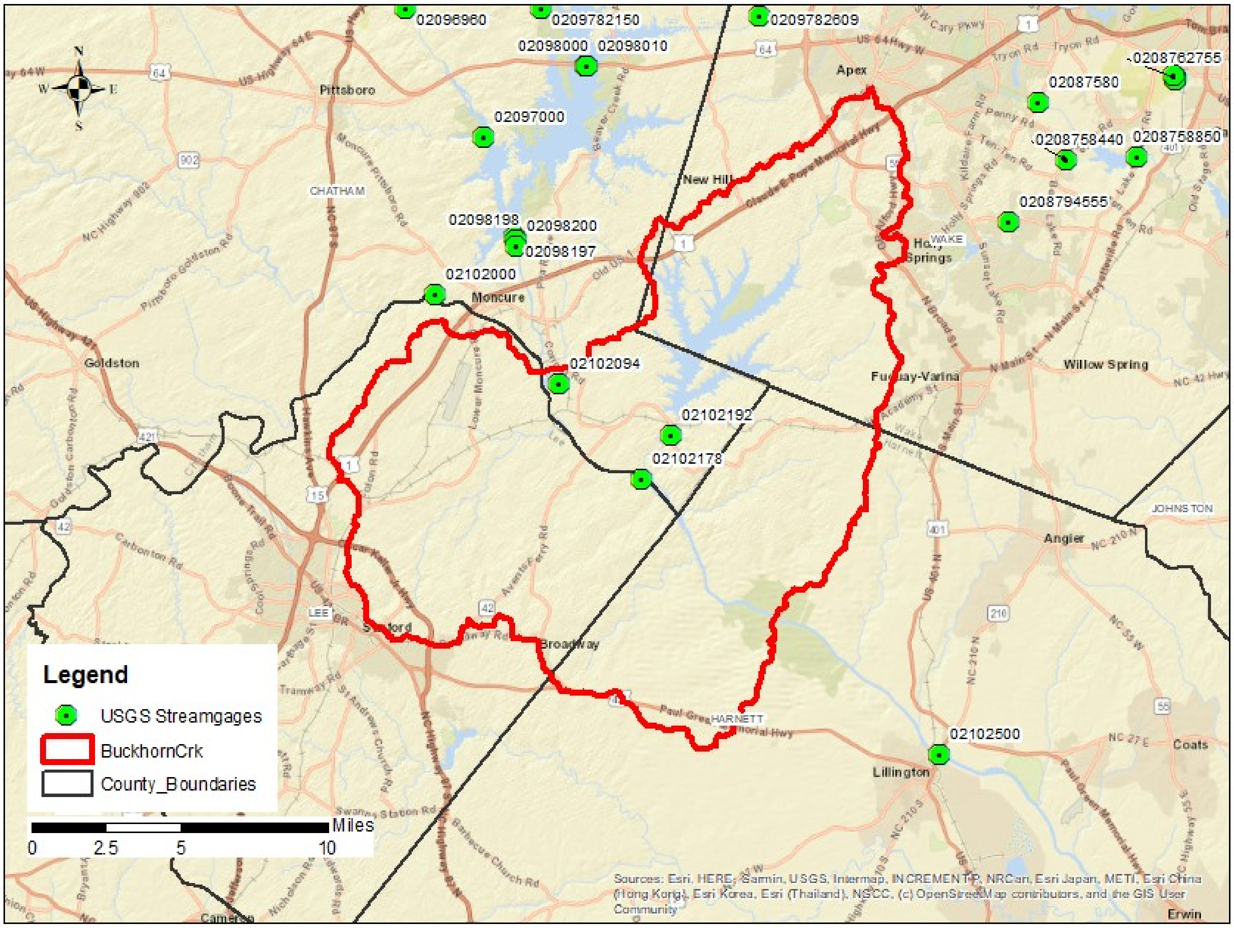


Figure 14:Location of USGS Streamgauges

5.2. Rainfall Data Development

5.2.1. Data Collection

5.2.1.1. General Circulation Model (GCM) Projections

Due to the nonstationarity of climate, future precipitation projections are needed for designing water infrastructure as climate conditions may be different at the end of the design life of the infrastructure than they are at present. Precipitation projections are usually derived from GCMs. There are multiple GCMs available, most of which provide projections that may be biased and, therefore, need to be downscaled to provide more accurate estimates. For this project, the Bias

Corrected Constructed Analogs (BCCA) V2 Daily Climate Projections (Bracken, 2016) was used. This data contains projections of daily BCCA CMIP3 and CMIP5 projections of precipitation for the contiguous United States that have been bias-corrected. These projections are available from USGS (https://labs.waterdata.usgs.gov/gdp_web/) for the time period of 1950 to 2100. The data can be assessed directly as weighted or unweighted area grid statistics using the link **https://cida.usgs.gov/thredds/.** The grid resolution is 0.125 degrees by 0.125 degrees. Depending on the period for which projections are needed, data can be downloaded as either:

- Bias Corrected Constructed Analogs V2 Daily Historical CMIP5 Climate Projections, or
- Bias Corrected Constructed Analogs V2 Daily Future CMIP5 Climate Projections

5.2.1.2. Historical Rainfall Data

Historical rainfall data is needed to downscale the rainfall projections from GCMs. Historical observed data is available from the USGS (https://labs.waterdata.usgs.gov/gdp_web/) and can be assessed as weighted or unweighted area grid statistics, similar to the climate projections. This allows for a one-to-one comparison of the projections with observed data to assess the accuracy of the projections and provide insights into the need for downscaling the projections. The historical data are daily gridded observations for the years 1950 through 2010 (Maurer et al., 2002).

5.2.2. Flood Frequency Analysis

Flood Frequency analysis of the historical forecast (1950-1999), historical rainfall data (1950 – 1999), and future precipitation data (2000-2100) was performed using the HEC-SSP program. HEC-SSP is a program developed by the USACE that is based on technical procedures documented in the USGS Bulletin 17C (England et al., 2019). Many frequency distributions, including the GEV and log-normal distributions, are available within HEC-SSP.

The GEV distribution method is often used to model heavy precipitation events. It requires three parameters: the location parameter (μ), which corresponds to the location of the distribution; the scale parameter (σ), which corresponds to the spread of the distribution; and the shape parameter (ξ), which determines the shape of the tail of the distribution. The GEV distribution can capture different types of extreme behavior, such as heavy-tailed, light-tailed, or bounded behavior, making it a useful tool for modeling the extreme values of precipitation. The three-parameter requirement for the GEV implies the need for long record lengths, which may not always be available.

The Log-normal distribution is a two-parameter distribution that describes the logarithm of the precipitation data as a normal distribution. The logarithmic transformation can help to normalize the precipitation data that is often positively skewed. The Log-normal distribution is more data parsimonious and hence more useful when long records are not available. This distribution does well when used to model the lower and middle portions of the precipitation distribution but may miss extreme tails.

The selected distribution depends on how well a particular distribution fits the data. HEC-SSP utilizes the Kolmogorov-Smirnov (US Army Corps of Engineers Hydrologic Engineering Center, 2019) Goodness of fit test to determine which distribution best fits the data. The data was tested against the Weibull plotting position. In applying these methods, both the GEV and the log-normal distributions provided convergence for all data sets and provided a good fit to the rainfall data compared to other distributions, as demonstrated by low Kolmogorov-Smirnov test scores (**Table 6**). However, the Kolmogorov-Smirnov scores for the GEV were slightly better than those for the log-normal distribution. The GEV distribution was therefore used for the data analyses. The HEC-

SSP results for the observed rainfall data, historical forecast, and future precipitation data are shown in **Figure 15, Figure 16, and Figure 17.**

Table 6: Kolmogorov-Smirnov Test Scores

	KOLMOGOROV-SMIRNOV TEST SCORES		
	Observed Precipitation	Historical Forecast	Future Forecast
GEV	0.083	0.106	0.062
Log-Normal	0.097	0.102	0.080

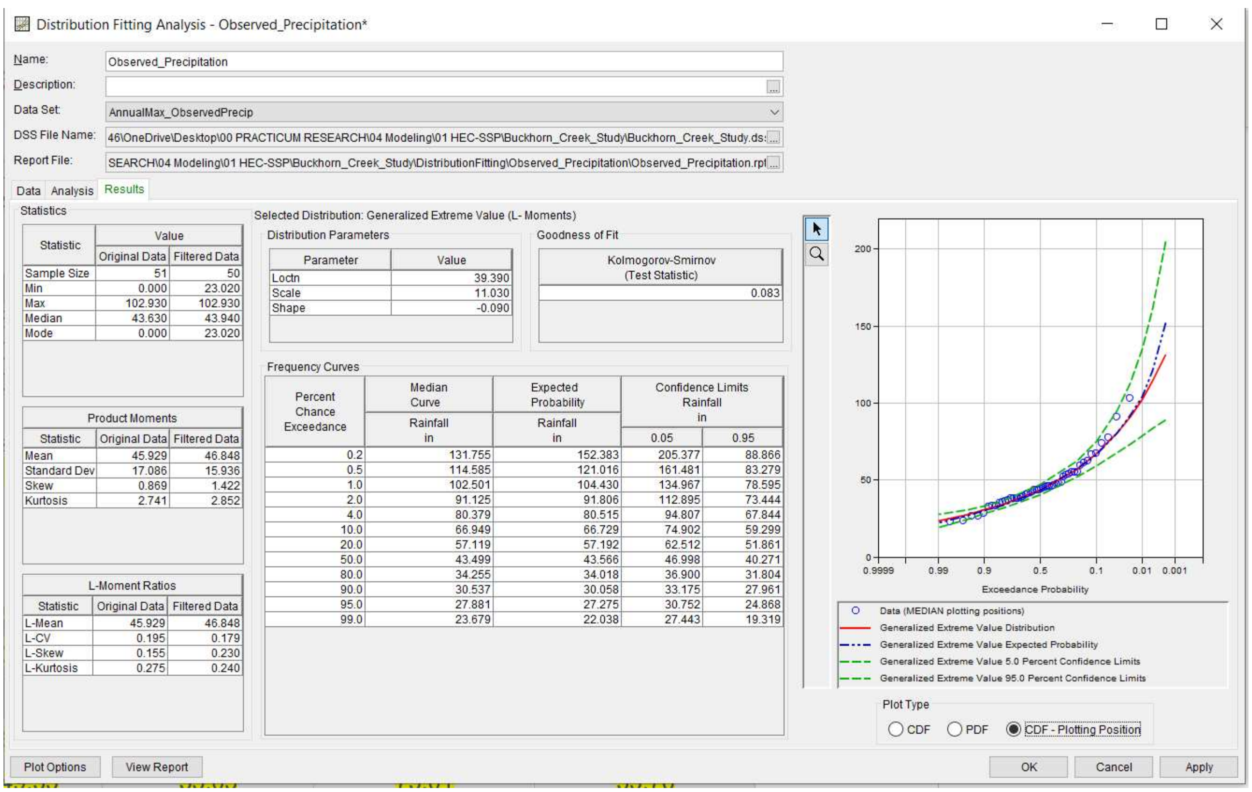


Figure 15: GEV Distribution for Observed Precipitation (1950-1999)

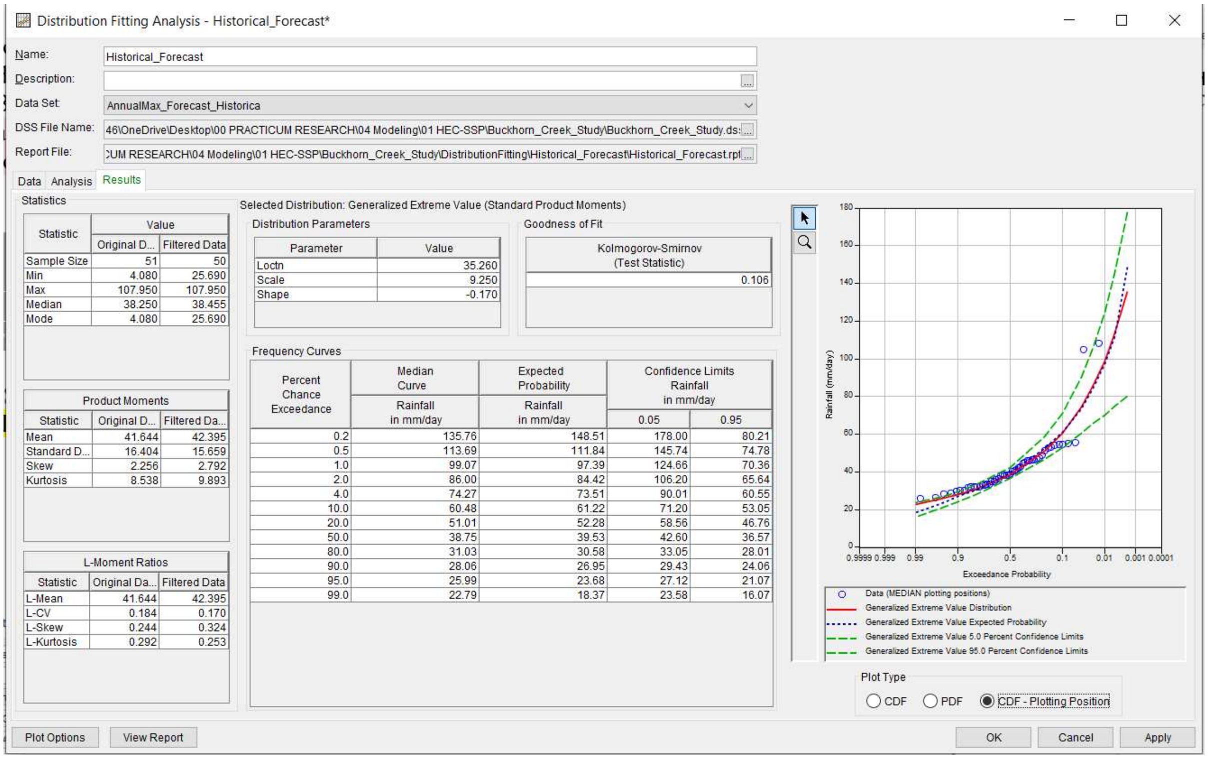


Figure 16: GEV Distribution for Historical Forecast (1950-1999)

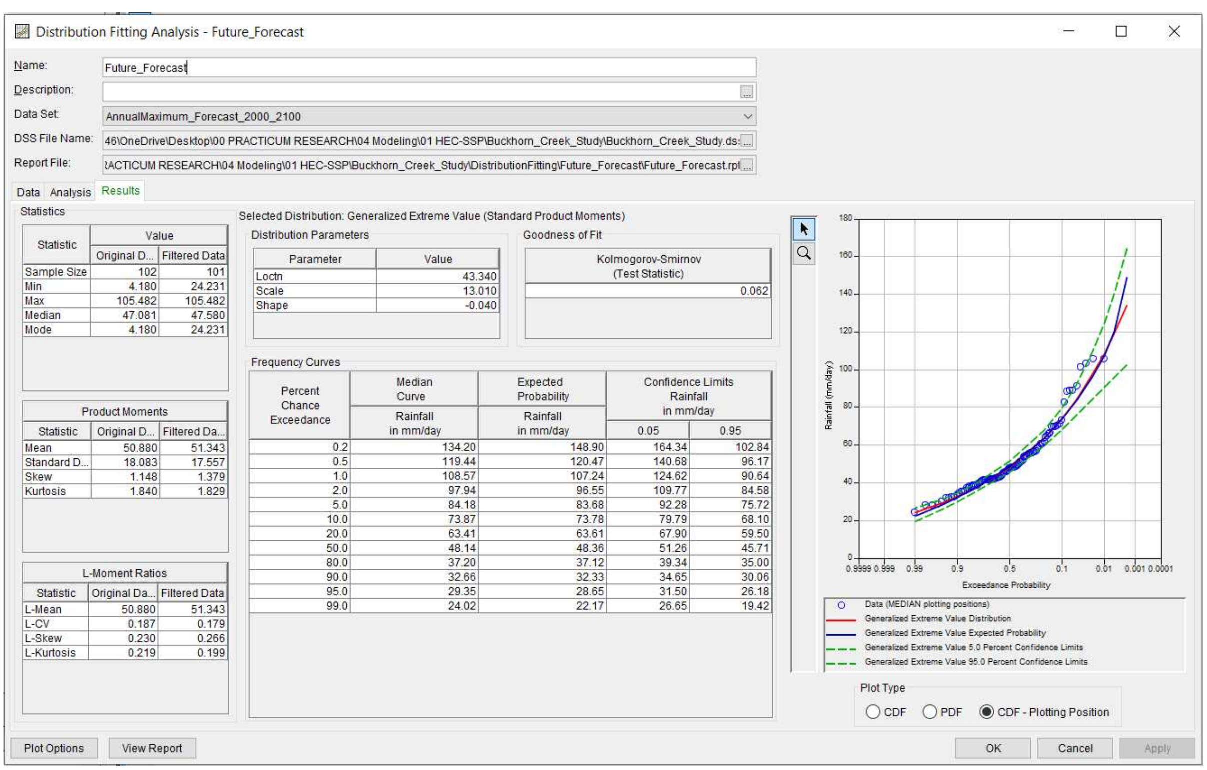


Figure 17: GEV Distribution for Future Forecast (2000-2100)

5.2.3. Climate Change Data and Statistical Downscaling

A comparison of the results between the observed data and the historical forecast (**Table 7**) indicates that the GCM projections generally underpredict rainfall amounts. The GCM forecasts, therefore, require further downscaling to improve their accuracy.

Table 7: Historical Forecast vs Observed Data

PERCENT CHANCE EXCEEDANCE	**OBSERVED DATA**			**HISTORICAL FORECAST**			**PERCENT CHANGE**
	Mean Curve	Confidence Intervals		Mean Curve	Confidence Intervals		
	mm/day	0.05	0.95	mm/day	0.05	0.95	
0.2	**131.8**	205.4	88.9	**135.8**	178.0	80.2	3%
0.5	**114.6**	161.5	83.3	**113.7**	145.7	74.8	-1%
1	**102.5**	135.0	78.6	**99.1**	124.7	70.4	-3%
2	**91.1**	112.9	73.4	**86.0**	106.2	65.6	-6%
4	**80.4**	94.8	67.8	**74.3**	90.0	60.6	-8%
10	**66.9**	74.9	59.3	**60.5**	71.2	53.1	-10%
20	**57.1**	62.5	51.9	**51.0**	58.6	46.8	-11%
50	**43.5**	47.0	40.3	**38.8**	42.6	36.6	-11%

Using Microsoft Excel, an equation that relates the rainfall estimates based on the observed data to that from the GCM outputs was developed (See **Figure 18**). In **Figure 18**, the Y-axis is the rainfall estimate based on observed data and the X-axis are the rainfall estimate based on the GCM outputs. As demonstrated by the high R^2 value of the trend line (0.9943), there is a strong linear relationship between the rainfall estimates based on the observed data and those derived based on the GCM outputs. The relationship between the rainfall estimates for various recurrence intervals based on observed data (Y) and those based on the GCM outputs (X) is defined as:

$$Y = 0.9702x + 5.0157$$

This relationship (Adjustment Equation) was used to estimate the expected 24-hour rainfall totals in the year 2000 (**Table 8**). A comparison between the estimates based on the adjustment equation and estimates based on the observed data is shown in **Table 9**. The adjustment equation yields estimates within 5-percent of the estimates based on the observed data.

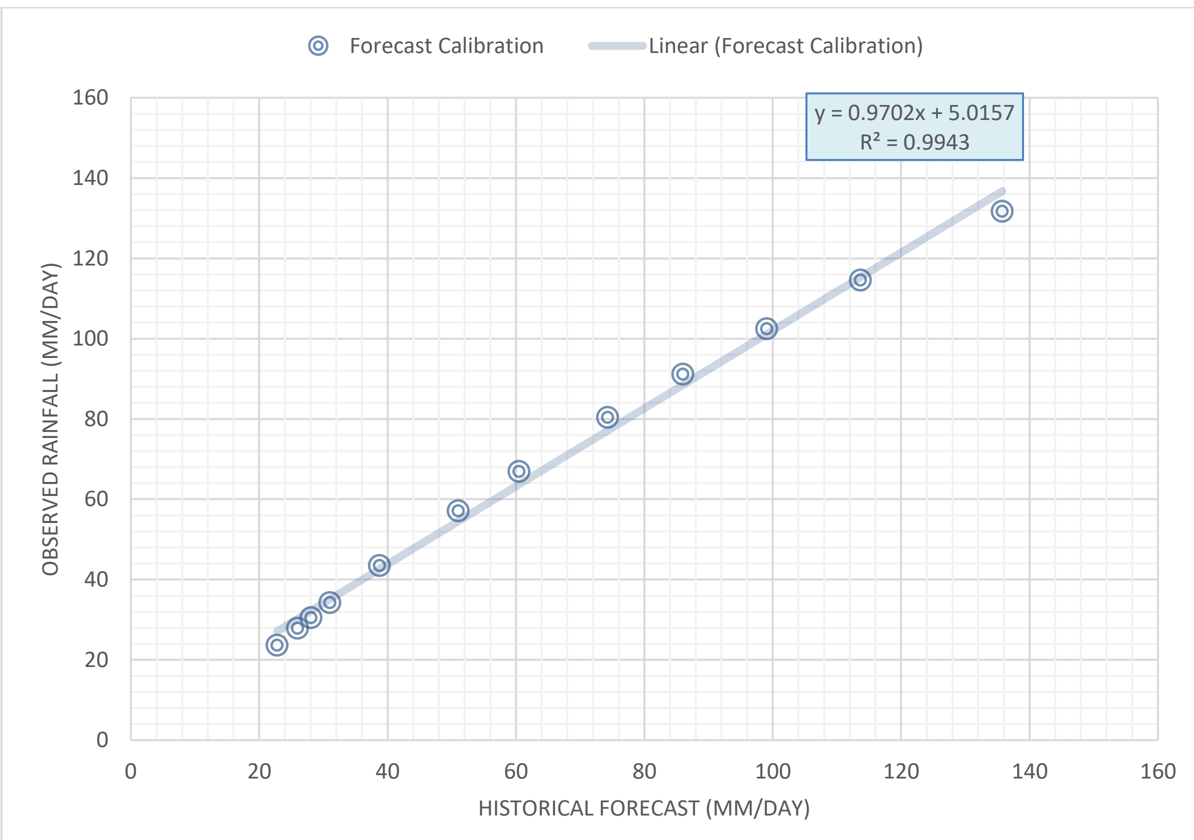


Figure 18: Forecast Calibration

Table 8: Predicted 2000 Rainfall Estimates

Percent Chance Exceedance	**Estimates based on GCM Projections**	**Estimates based on Adjustment Equation**	
	mm/day	mm/day	inches/day
0.2	135.76	**136.73**	**5.38**
0.5	113.69	**115.32**	**4.54**
1	99.07	**101.13**	**3.98**
2	86	**88.45**	**3.48**
4	74.27	**77.07**	**3.03**
10	60.48	**63.69**	**2.51**
20	51.01	**54.51**	**2.15**
50	38.75	**42.61**	**1.68**

Table 9: Observed vs Adjusted Estimates for 2000

Percent Chance Exceedance	**2000 Estimates Based on Observed Data**	**2000 Estimates based on Adjustment Equation**	**Difference**
	inches/day	inches/day	%
0.2	5.19	5.38	4%
0.5	4.51	4.54	1%
1	4.04	3.98	-1%
2	3.59	3.48	-3%
4	3.16	3.03	-4%
10	2.64	2.51	-5%
20	2.25	2.15	-5%
50	1.71	1.68	-2%

The adjusted projected rainfall estimates for 2100 are shown in **Table 10**. The results indicate that the expected changes in rainfall trends vary based on the recurrence interval being considered. Rainfall estimates remain virtually unchanged for the 500-year event (least frequent event), while the more frequent events (2 to 10 years) are expected to increase by 20 to 22-percent.

Table 10: Predicted 2100 Rainfall Estimates

Percent Chance Exceedance	**Return Period (Years)**	**Mean Curve**	**Adjusted Estimates**		**% Change in Rainfall Estimates (2000 to 2100)**
		mm/day	mm/day	inches/day	
0.2	**500**	134.2	**135.22**	**5.32**	-1%
0.5	**200**	119.44	**120.90**	**4.76**	5%
1	**100**	108.57	**110.35**	**4.34**	9%
2	**50**	97.94	**100.04**	**3.94**	13%
4	**25**	84.18	**86.69**	**3.41**	12%
10	**10**	73.87	**76.68**	**3.02**	20%
20	**5**	63.41	**66.54**	**2.62**	22%
50	**2**	48.14	**51.72**	**2.04**	21%

5.2.4. Results and Discussion

The approach described in Sections 5.2.2 and 5.2.3 yields rainfall estimates, in terms of Annual Exceedance Probabilities (AEPs), for a future climate. The approach involves developing a relationship (fit) between the rainfall estimates based on observed data and those based on GCM outputs. The fit is then applied to correct rainfall estimates developed based on GCM outputs for a future period. The fit can be updated as more historical data becomes available.

The results of the analysis for the Buckhorn Creek basin (Table 10) indicate that design rainfall amounts in the year 2100 are expected to increase when compared to the estimates in the year 2000. The increases are more significant for the more frequent events (20 to 22 percent for the 2-year, 5-year, and 10-year events to almost no change for the 500-year event). This is indicative of the fact that predictive accuracy decreases as one moves further into the future due to the increase in uncertainty and the limited available observed data for estimating the fit.

As indicated in Chapter 3, a combination of the flood frequency methods and an adaptive management framework provides a practical means for accounting for nonstationarity. Based on the adaptive management framework put forward in Chapter 4, the fit should be adjusted every other year to account for additional observed data. Rainfall estimates for the future period should also be estimated using updated GCM outputs every other year. The combination of the updated fit between observed data and GCM outputs and future rainfall estimates, based on updated GCM outputs, helps minimize the uncertainty associated with the future rainfall estimates.

5.3. Hydrologic and Hydraulic Model Development

5.3.1. Data Collection

Terrain data, rainfall Data, Soil data, land cover data, hydraulic structures data, and observed rainfall and streamflow data for calibration were needed to develop the hydrologic and hydraulic (H&H) model. This section describes the data sources used to develop the H&H model for the Buckhorn Creek basin.

5.3.1.1. Terrain Data

Quality Level II (QL2) lidar data collected by North Carolina Emergency Management (NCEM) in early 2014 and 2015 was used. The data is available in the NAD 1983 (2011) State Plane North Carolina FIPS 3200 (US Feet) coordinate system with a vertical datum of NAVD88 in feet. Digital Elevation Models (DEMs), developed from the QL2 data, with cell sizes of 10 feet were used for the hydraulic model development.

5.3.1.2. Rainfall Data

Rainfall estimates are based on the estimates developed in **Section 5.2**. The rainfall estimates developed in **Section 5.2** represent expected design rainfall estimates for a given return period. For hydrologic modeling in HEC-RAS, the total rainfall estimates need to be distributed over a 24-hour duration. The SCS Type II rainfall distribution was used to distribute the total 24-hour duration rainfall data for simulations related to Peakflow analysis. The Type II distribution (**Figure 19**) is the expected distribution for North Carolina (USDA-SCS, 1986). For simulations related to volume assessment, the 24-hour estimate was distributed evenly over the 24-hour period.

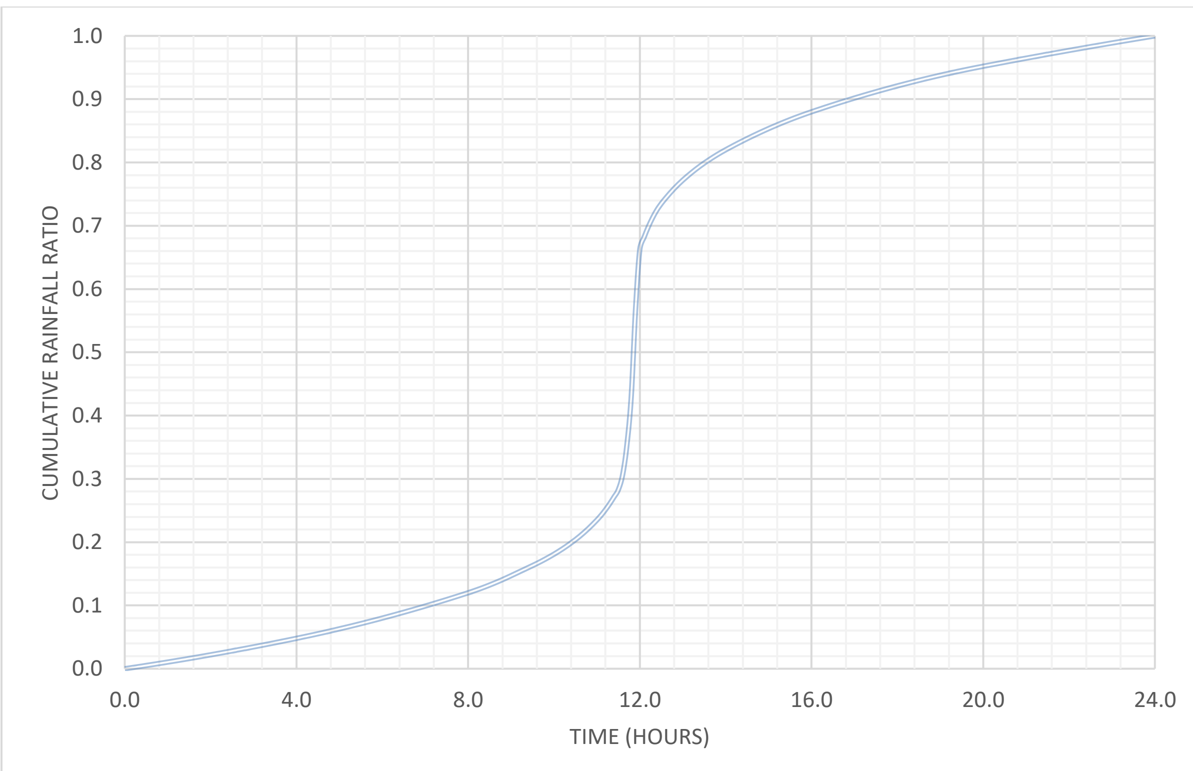


Figure 19: SCS Type II 24-Hour Rainfall Distribution (USDA-SCS, 1986)

5.3.1.3. Soil Data

Soil data was acquired from the Natural Resources Conservation Service (NRCS) Soil

Survey Geographic Database (https://websoilsurvey.nrcs.usda.gov/app/WebSoilSurvey.aspx). **Figure 16** shows the Hydrologic Soil Groups (A, B, C, and D) within the basin. Hydrologic Soil Groups indicate the infiltration capacities of soils, with A soils being the most permeable and D soils being the least permeable. All four hydrologic soil groups exist within the Buckhorn Creek basin (**Figure 20**).

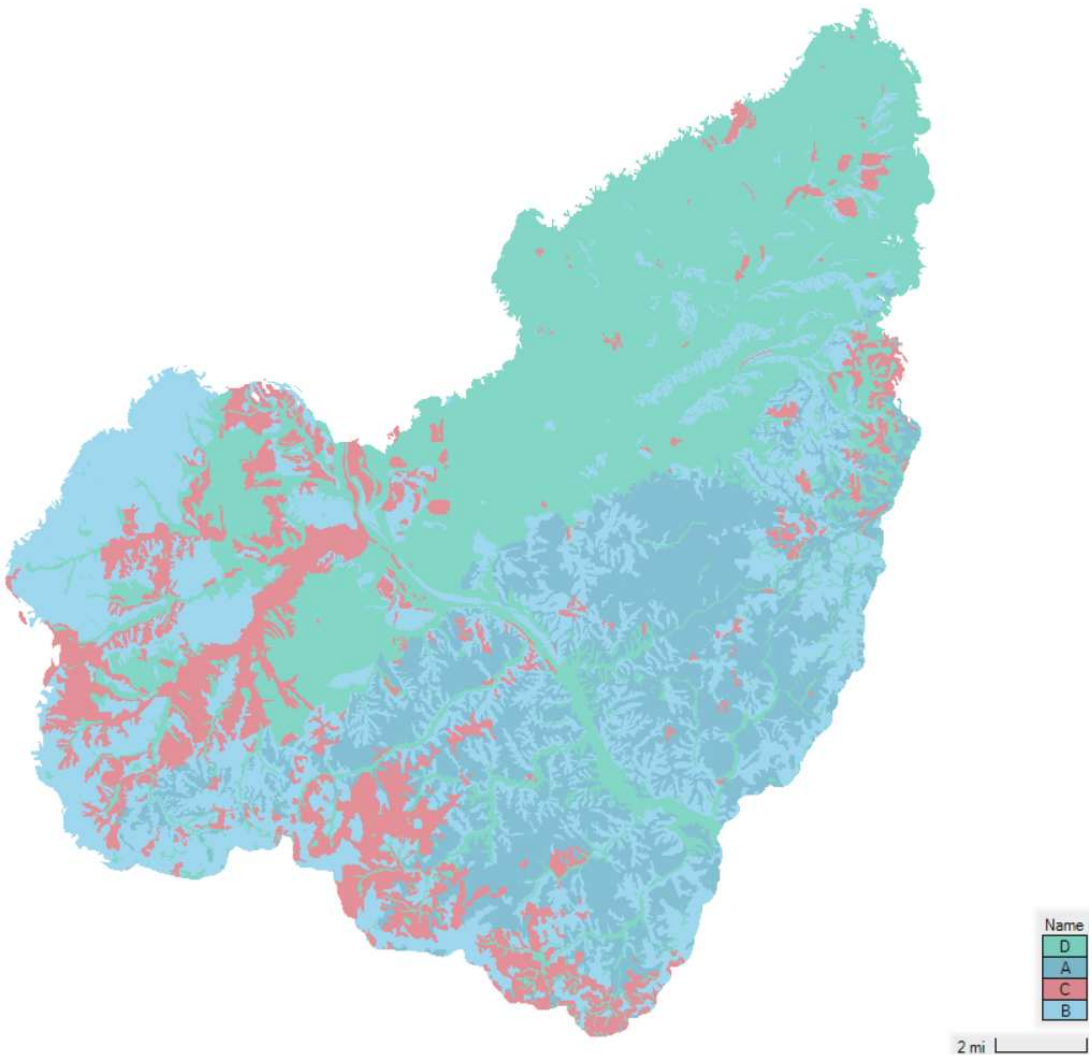


Figure 20: Buckhorn Creek Basin Hydrologic Soil Groups

5.3.1.4. Land Cover Data

Land cover data is needed, in addition to soil data, to estimate infiltration rates. Land cover data described in **Section 5.1** was used. The various landcover types within the Buckhorn Creek basin are shown in **Figure 21**.

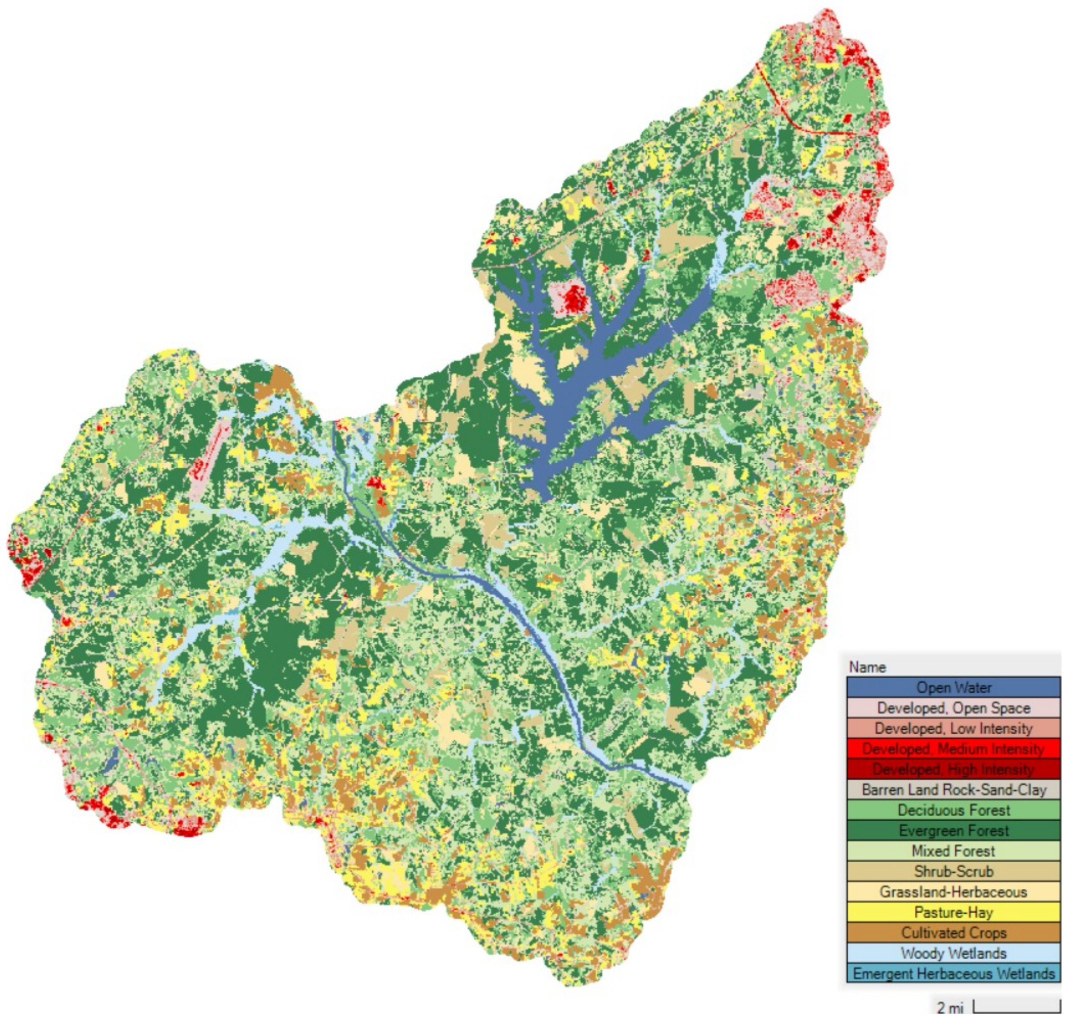


Figure 21: Buckhorn Creek Basin NLCD Landcover Types

5.3.1.5. Hydraulic Structures Data

Hydraulic structures data (culverts and bridges) are needed to hydro-correct the terrain data. The QL2 Lidar data does not accurately capture hydraulic structure openings. Using the uncorrected terrain will result in inaccurate flow paths within the model. Information on hydraulic structures was obtained from Google Earth imagery. Prior to using the terrain data for modeling, notches were created in the lidar data to represent the hydraulic structures' openings. The sizes of the notches were based on the sizes of the hydraulic structure opening.

5.3.1.6. Observed Data

Rainfall data for Hurricane Florence is available at USGS Gauge 02098197, Everett Jordan Lake, NC. Streamflow and stage data for Hurricane Florence are available at USGS gauge 02102192 (Buckhorn Creek NR Corinth, NC) and USGS gauge 02102500 (Cape Fear River at Lillington, NC). Streamflow and stage data at these gauges were downloaded and used for model performance verification.

5.3.2. Data Development

5.3.2.1. Basin Delineation

One of the inputs for hydrological modeling is the basin area. The basin area represents the contributing catchment at the outlet point of the basin. Accurate basin delineation is essential as the basin area is directly proportional to flow rates. The basin for the Buckhorn Creek Basin was delineated using the terrain data described in **Section 5.3.1.1.**

5.3.2.2. Curve Number Development

The Curve Number (CN) method was the adopted method for modeling infiltration. The CN method is an empirical surface runoff method developed by the US Department of Agriculture (USDA) Natural Resources Conservation Service (NRCS), formerly the Soil Conservation Service (SCS 1986). The SCS CN method estimates precipitation excess as a function of the cumulative precipitation, soil cover, land use, and antecedent soil moisture.

CN values range from approximately 30 (for permeable soils with high infiltration rates) to 100 (for water bodies, impervious surfaces, and soils with near zero-infiltration rates). Publications from the Soil Conservation Service (1971, 1986) provide further background and details on the use of the CN model.

CN values for the Buckhorn Creek basin were developed based on the soil data and the land use data. **Table 11** shows the curve number matrix used to estimate curve numbers. These values are based on average moisture conditions for the soil (ARC II). In cases where soils are designated with dual Hydrologic Soil Groups A/D, B/D, or C/D, an average Curve Number was determined using the two Hydrologic Soil Groups identified. A raster file with CN values for each combination of land cover and hydrologic soil group was developed and used for the HEC-RAS modeling. The CN grid is shown in **Figure 22**.

Table 11: Curve Numbers for Associated Land Cover and Hydrologic Soil Group (AMC II)

Land Cover	**Hydrologic Soil Group**			
	A	B	C	D
Barren Land	63	77	85	88
Cultivated Crops	64	75	82	85
Deciduous Forest	36	60	73	79
Developed, High Intensity	89	92	94	95
Developed, Low Intensity	51	68	79	84
Developed, Medium Intensity	61	75	83	87
Developed, Open Space	39	61	74	80
Evergreen Forest	30	55	70	77
Grassland	49	69	79	84
Hay/Pasture	39	61	74	80
Herbaceous Wetlands	72	80	87	93
Mixed Forest	36	60	73	79
Open Water	99	99	99	99
Shrub/Scrub	35	56	70	77
Woody Wetlands	36	60	73	79

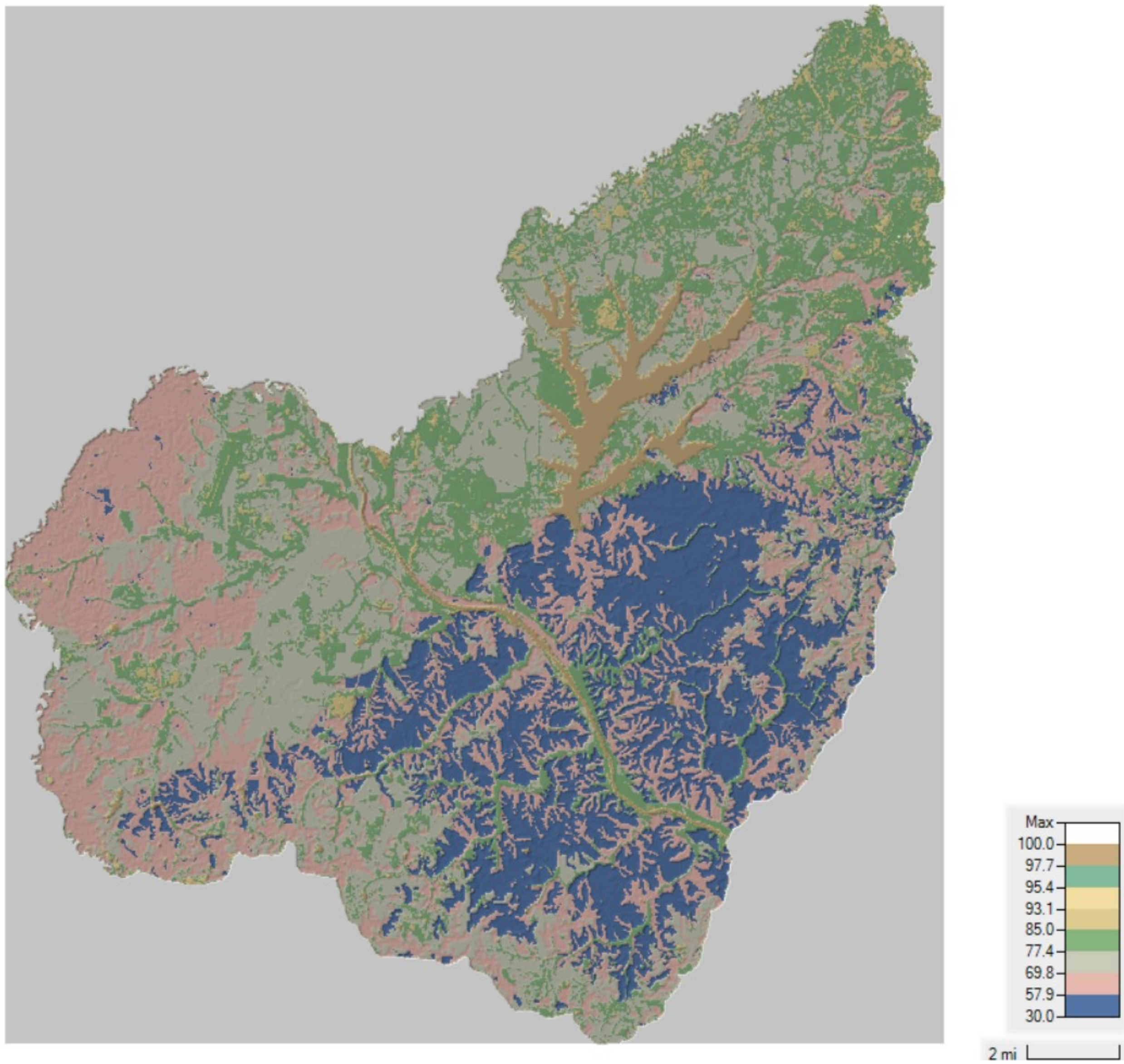


Figure 22: Buckhorn Creek CN Grid

5.3.2.3. Manning's N Development

The Manning's n-values used in the model development are shown in **Table 12**. These values are based on various published references accepted by the engineering community (Chow, 1959) and the land cover data. A raster file with Manning's n-values for each land cover class was developed and used for the HEC-RAS modeling. The Manning's n-value grid is shown in **Figure 23**.

Table 12: Manning's n-value Summary for HEC-RAS Model Development

NLCD Value	Recommended n-value	Range of n-values	Description
11	0.03	0.025-0.05	Open Water
21	0.04	0.03-0.05	Developed, Open Space
22	0.1	0.08-0.12	Developed, Low Intensity
23	0.12	0.06-0.14	Developed, Medium Intensity
24	0.15	0.12-0.20	Developed, High Intensity
31	0.03	0.023-0.03	Barren Land (Rock/Sand/Clay)
41	0.13	0.10-0.16	Deciduous Forest
42	0.13	0.10-0.16	Evergreen Forest
43	0.13	0.10-0.16	Mixed Forest
52	0.1	0.07-0.16	Shrub/Scrub
71	0.045	0.025-0.05	Grassland/Herbaceous
81	0.06	0.025-0.06	Pasture/Hay
82	0.06	0.025-0.06	Cultivated Crops
90	0.12	0.045-0.15	Woody Wetlands
95	0.08	0.05-0.085	Emergent Herbaceous Wetlands

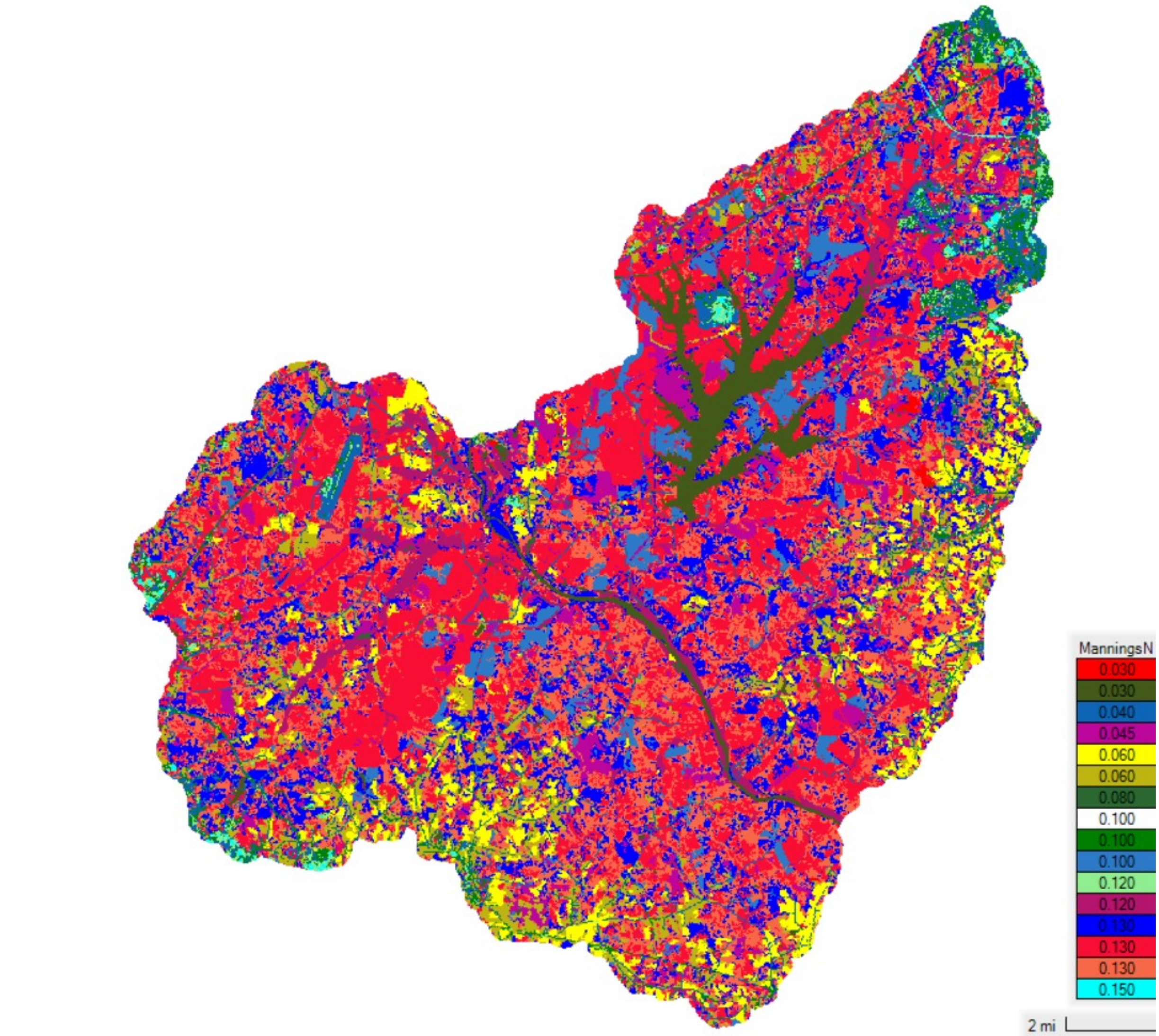


Figure 23: Buckhorn Creek Manning's N Grid

5.3.3. *Model Development*

5.3.3.1. *Modeling Software Selection*

A 2-dimensional rain-on-grid modeling approach was employed for the hydrologic and hydraulic (H&H) model development. The H&H model was developed using the public domain United States Army Corps of Engineers (USACE) HEC-RAS model (version 6.3.1). HEC-RAS was chosen for the following reasons:

a) HEC-RAS can be used for both hydrologic and hydraulic analysis.

b) Runtimes for HEC-RAS are considerably faster than other available model options.

c) HEC-RAS is free and hence will provide cost savings compared to other commercially available models.

Capabilities of the HEC-RAS software relevant to this study include:

- 2D modeling ability
- Flexible mesh
- Variable timestep
- Rain-on-grid modeling ability
- Ability to model hydraulic structures in 2D domains
- Ability to model infiltration and other losses
- Ability to use spatially varying rainfall
- Ability to directly create and export floodplains as GIS files

5.3.3.2. Geometry Data (Mesh) Development

The delineated Buckhorn Creek basin watershed was buffered and used as the model domain. The hydro-corrected terrain data described in Section 5.3.1.5 was the main input for building the 2D model geometry data. Roadways and other topographic features within the basin were defined as break lines (polylines used with HEC-RAS to delineate a specific boundary to which the 2D mesh should triangulate) within the computational mesh to capture topographic features that may impact the hydrology and hydraulics. Other inputs for the geometry data are the CN and Manning's n-value grids. The CN and Manning's N grids described in Section 5.3.2 were imported into the mesh.

The mesh was configured to model all the key features within the Buckhorn Creek basin. These features include:

- Shearon Harris Lake
- Sharon Harris Dam
- Buckhorn Dam
- Impoundment behind Buckhorn Dam

The Shearon Harris Lake was modeled as a reservoir using the storage area feature within HEC-RAS. The entire contributing drainage area at the location of the Shearon Harris Dam was modeled as a reservoir. The storage area feature required elevation-volume data. The elevation-volume data was developed based on the terrain data. The initial pool elevation was based on the spillway crest elevation of the Shearon Harris Dam.

The Shearon Harris Dam was modeled using the 2D connection feature in HEC-RAS. The dam and spillway crest elevations were derived from the terrain data. The 2D connection representing the Shearon Harris Dam connects the Shearon Harris Lake to the downstream area which includes the Cape Fear River.

The Buckhorn Dam was also modeled using the 2D connection feature in HEC-RAS. The dam crest elevation was derived from the FEMA effective model for the Cape Fear River.

The terrain data behind the Buckhorn Dam was modified to reflect the available storage area behind the dam. The streambed elevation needed for the modification was derived from the FEMA effective model for the Cape Fear Basin. Modification of the terrain to reflect the storage behind the dam is essential since that storage is used for water supply by the Town of Sanford, NC.

The HEC-RAS geometry data is shown in **Figure 24**.

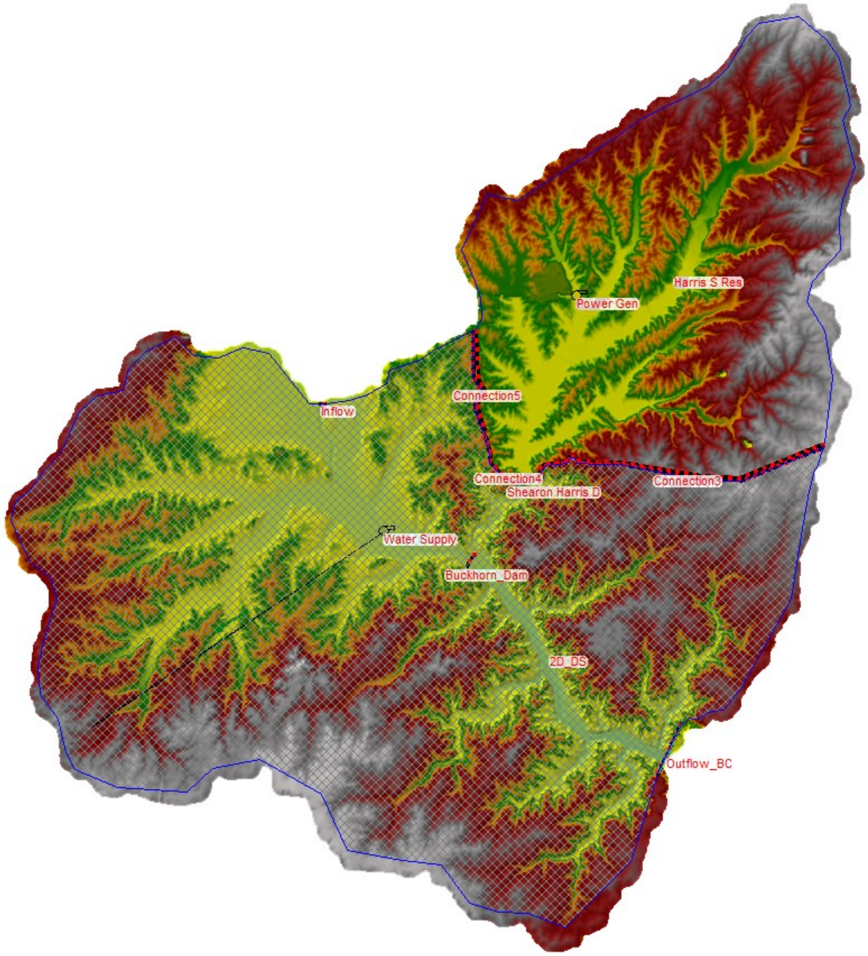


Figure 24: Buckhorn Creek HEC-RAS Geometry Data

5.3.3.3. Boundary Conditions

<u>*Inflow Boundary Condition / Rainfall Data*</u>

Rainfall data is a required data input for the 2-D rain-on-grid modeling approach. In HEC-RAS, the rainfall data, in the form of a hyetograph, is specified in the flow data component. The rainfall hyetographs described in **Section 5.3.1.2** were used for the analysis. The rainfall data represents rainfall within the Buckhorn Creek basin. Rainfall transformation into runoff in HEC-RAS, like most other rain-on-grid models, is based on the routing of excess rainfall from one grid cell to another.

Flow from the upstream basins into the Cape Fear River portion within the Buckhorn Creek basin was specified as a streamflow hydrograph. Since Jordan Lake attenuates almost all flows upstream of the Buckhorn Creek Basin, known releases from the Jordan Lake were used as inflows into the Cape Fear River reach within the Buckhorn Creek basin.

<u>Outflow Boundary Condition</u>

Two sets of outflow boundary condition lines were utilized within the model, one set drawn along the downstream and upstream ends of the Cape Fear River reach within the Buckhorn Creek Basin, and another drawn all along the 2D perimeter. The outflow boundaries at the upstream end of the Cape Fear River reach were necessary to prevent water ponding along the mesh boundary under high flow conditions. Since the perimeter of the 2D domain included an additional buffer area beyond the watershed on the upstream side, boundary condition lines were drawn along the upstream side to allow water from the buffer area to flow out of the system (out of the perimeter of the 2D domain). Normal depth was adopted as the outflow boundary condition at these locations within the models. The energy gradient slope, required as input for the normal depth boundary condition, was estimated based on the average stream or terrain slope in the vicinity of the boundary condition line.

5.3.3.4. Model Simulation

Within HEC-RAS, "plans" combine geometry data and flow data and specify the computational parameters such as computational timestep, hydrograph output interval, detailed output interval, simulation start date and time, and simulation end date and time.

HEC-RAS solves the Diffusion-Wave Equation (DWE) and Shallow-Water Equations (SWE). The DWE set is a simplification of the SWE set. The DWE considers the effect of only bed friction and flow surface slope and ignores the local and convective acceleration terms (effect of unsteadiness of flow and effect of contraction/expansion) that are part of the SWE set (USACE, 2021). These simplifications result in faster simulation times but may not provide accurate results in areas with significant flow expansion and contraction, such as bridge and culvert openings. The DWE equations were used for faster simulations.

5.3.3.5. Model Validation

The recorded rainfall in September 2018 during Hurricane Florence was simulated and the resulting flooding was compared to measured flows and stages at available USGS gauge locations within the pilot basin. Manning's n values were adjusted within reasonable ranges till the modeled flows and stages were comparable to the measured data at the USGS gauge locations.

USGS Gauge 02098197, Everett Jordan Lake, NC rainfall distribution was used for Hurricane Florence as shown in **Figure 25**. A comparison of the modeled flows and observed flows at USGS gauge 02102500, downstream end of pilot basin is shown in **Figures 26**. The parameters of interest are the predicted volume (area under the curves) and the predicted peak flow rates. Based on the visual inspection of **Figure 26**, the area under both the observed and predicted hydrographs are similar indicating that the predicted volume matches the observed volume. The observed peak flow rate is 62,500 cfs compared to a predicted peak flowrate of 61,150 cfs. The predicted peak flow rate is within 3% of the observed peak flow rate. The predicted lake levels and inundation areas from Hurricane Florence are shown in **Figure 27**.

The results indicate that the hydrologic and hydraulic models can be used to transform the precipitation data into design parameters (flow rate, volume, and elevation data) for the Buckhorn Creek Basin.

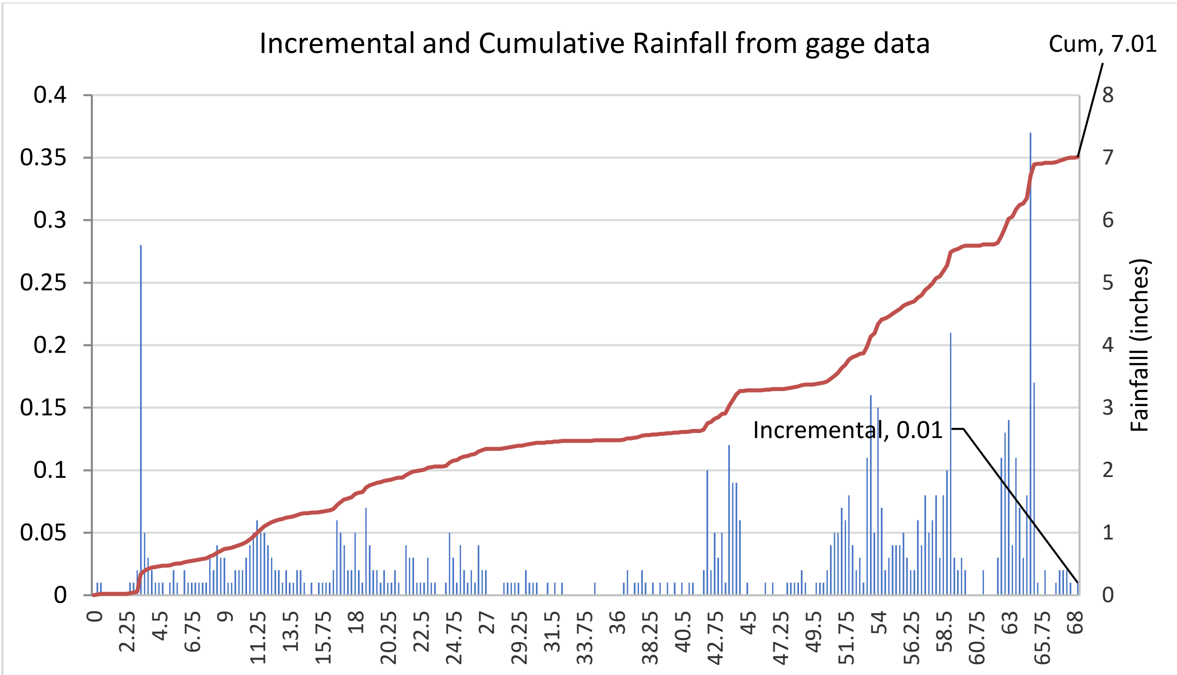


Figure 25: Hurricane Florence Rainfall Data at USGS Gauge 02098197, Everett Jordan Lake, NC

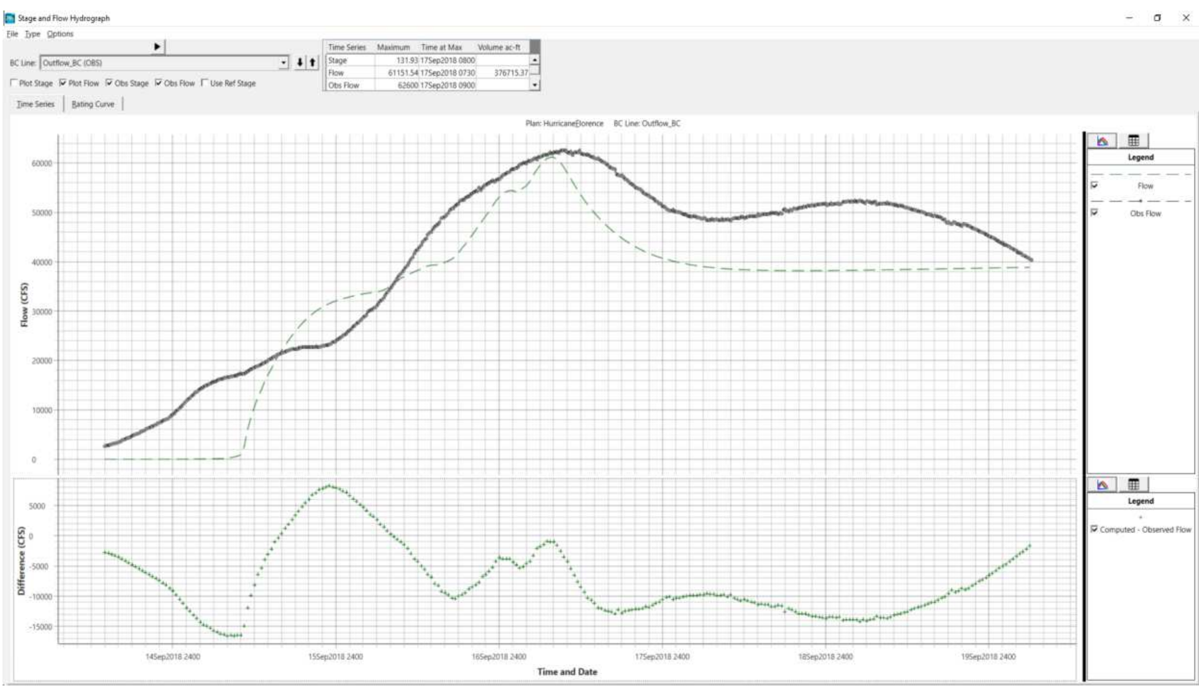


Figure 26: Modeled versus observed flows at USGS gauge 02102500 (Cape Fear River at Lillington, NC)

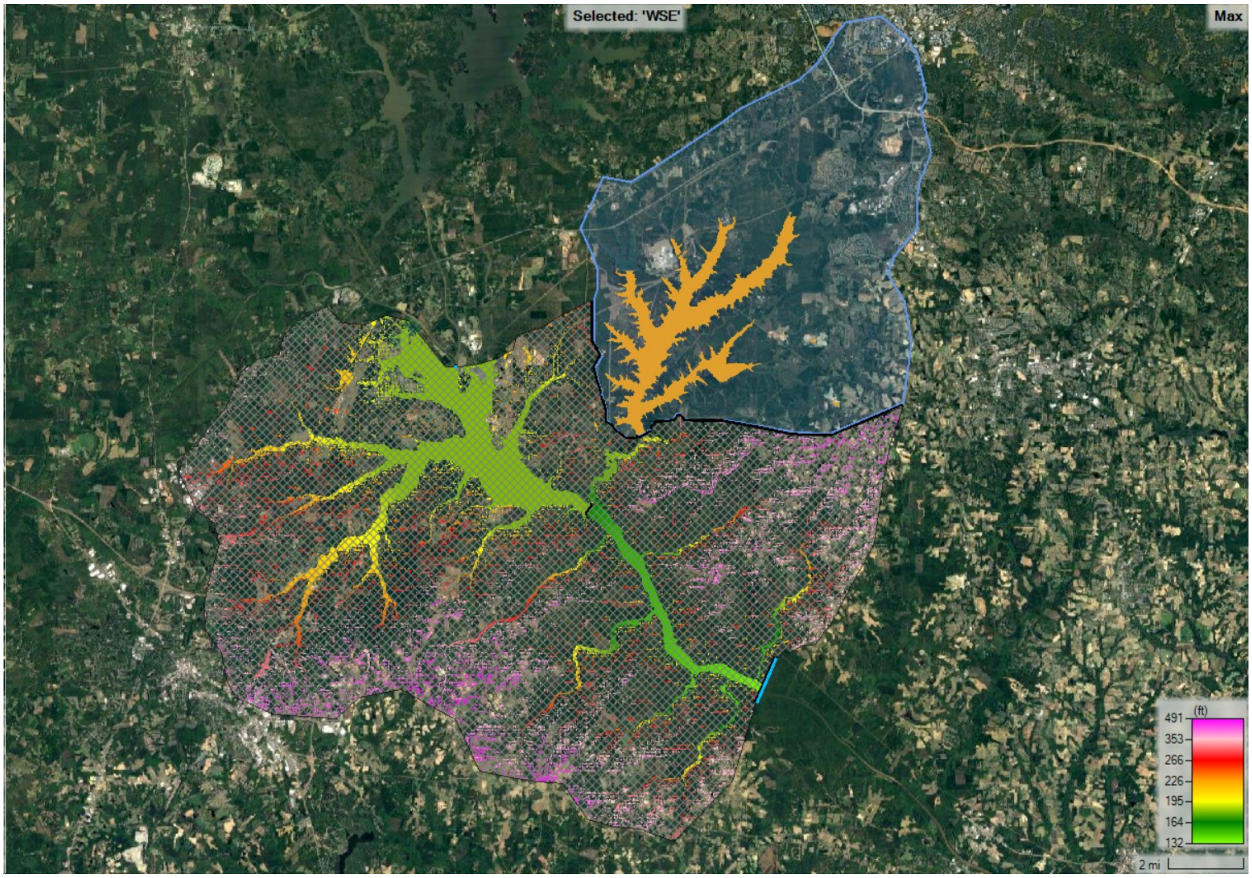


Figure 27: Modeled Lake Levels and Inundation Extents from Hurricane Florence

CHAPTER 6: HYBRID APPROACH TESTING AND SYSTEM VALIDATION

In this chapter, the hybrid approach detailed in Chapters 3, 4 and 5 are implemented for the pilot basin. Stakeholder-informed performance metrics are then used to evaluate the performance of the new approach as compared to the traditional approach. This chapter addresses Research Question 4, which is restated below:

Research Question 4: How does the new approach that accounts for nonstationarity and multiple objectives compare to the traditional approach?

As noted in **Chapter 4**, an **adaptive management framework** that defines and maintains baseline objectives of existing basin users while designing the primary water infrastructure in a manner that accounts for nonstationarity and uncertainty is proposed for designing and managing water infrastructure in multi-use basins. The adaptive management approach allows for regular review and refinement of the application of climate data and allows for adjustments to basin objectives, thereby reducing uncertainty within the data needed for decision-making.

The subsequent sections demonstrate how such an approach can be implemented. An assessment of the performance of the proposed approach, based on pre-defined performance metrics, is also provided.

6.1. Performance Metrics

As noted in Chapters 1 through 3, traditional approaches for designing and managing water infrastructure in multi-use basins do not adequately account for non-stationarity due to climate change. Traditional approaches also only focus on the water infrastructure being designed without considering impacts on other basin users. The success of the proposed approach is dependent on its ability to address the shortcomings of existing traditional approaches. It is, therefore, necessary to define metrics that can be used to assess the performance of the proposed approach in comparison with that of the traditional approach.

To develop the performance metrics, multiple structured interviews with water practitioners were conducted. Indirect stakeholder engagement was also done. The process of arriving at the performance metrics is described in the subsequent sub-sections.

6.1.1. Structured Interviews

Initial interviews were conducted with members of the research advising committee: Michael DePue, PE, CFM, PMP, a principal water resources engineer at AtkinsRéalis, with 26 years of experience in water infrastructure design and management and Dr. Steve Conrad, associate professor of systems engineering at Colorado State University, with 26 years of experience in the water sector, including experience serving on the board of directors for three water associations in Canada and the United States. Additionally, discussions with colleagues within this researcher's water network and managers within the pilot basin were also done. The purpose of the structured interviews was to get answers to the following questions:

1. *What are the linkages between the various basin uses and stakeholders and how does one use impact another?*
2. *How can the impact of one basin use on another be quantified?*
3. *What metrics define the performance of each basin use?*

Responses to these questions are summarized below.

Relationship between various basin uses and the impact of each basin use on another.

The Buckhorn Creek basin has three main uses. These uses are tied to the Shearon Harris Reservoir, the Buckhorn Dam and the Cape Fear River. The Buckhorn Dam impounds water on the Cape Fear River for water supply for the Town of Sanford, NC. The Buckhorn Dam is a run-of-river dam on the Cape Fear River. Discharges from the Jordan Lake that are not extracted for water supply flow downstream over the Buckhorn Dam.

The Shearon Harris Reservoir is an impoundment on Buckhorn Creek which serves as the cooling water source for the Shearon Harris Power Plant. The Shearon Harris Reservoir is also used for recreation (Boating and Fishing). The Buckhorn Creek is a tributary to the Cape Fear River. Discharges from the Shearon Harris Reservoir flow into the Cape Fear River at the confluence of Buckhorn Creek and Cape Fear River, just downstream of the Buckhorn Dam.

The total flow within the Cape Fear River downstream of its confluence with the Buckhorn Creek is the combination of the flows over the Buckhorn Dam and Releases from the Shearon Harris Reservoir. Meeting the environmental flow requirements for the Cape Fear River, therefore, depends on the design and operation of the Buckhorn Dam for water supply uses and the Shearon Harris Dam and Reservoir for power generation use. Additionally, excessive discharges from the Shearon Harris and Buckhorn Dams could result in high water levels within the Cape Fear River that could cause flooding damage to several critical facilities along the Cape Fear River.

Quantification of the impact of one basin use on another.

All the basin uses are impacted by or impact the Cape Fear River. Measuring flows in the Cape Fear River downstream of its confluence with the Buckhorn Creek provides a quantitative way of assessing the impacts of one basin use on another. For this to be possible, the entire basin and all the basin uses need to be modeled in the hydrologic and hydraulic model. This will allow for a quantitative assessment of the impacts of withdrawals for water supply use and water consumed for cooling in the process of generating power on the flows in the Cape Fear River.

Performance Metrics for Each Basin Use

Water Supply: Water supply relates to the quantity of water needed to meet the water supply needs of the basin user(s). One of the metrics for water supply is, therefore, the minimum water withdrawal to meet the water supply needs. Withdrawals for water supply needs rely on intake pipes that are set at known elevations. Water cannot be withdrawn for water supply needs once the river stage falls below the intake elevation. The minimum river stage is, therefore, another metric for water supply. The metrics for water supply are summarized in **Table 13**.

Power Generation: The Shearon Harris Power Plant is a nuclear power plant. Nuclear power plants use water in three major ways: extracting and processing uranium fuel, producing electricity, and controlling wastes and risks. Although most of the water for cooling may be returned to the lake, some of the water is permanently lost through evaporation. The amount of water consumed/lost through evaporation is, therefore, a metric for power generation.

Like the process for water supply, flows needed for cooling are withdrawn through an intake pipe set at a known elevation. Water cannot be withdrawn once the reservoir elevation falls below the intake elevation. The intake elevation is, therefore, a metric for power generation as it represents the minimum required elevation within the reservoir. The metrics for power generation are summarized in **Table 13**.

Recreation: The use of the Shearon Harris Reservoir as a recreational resource is dependent on the lake levels. The lake cannot be used for recreation if the lake level is either too high or too low. Lake levels are, therefore, a metric for recreational use. The metric for recreation is included in **Table 13**.

Environmental Flows: Environmental flows represent the minimum regulated flows within the Cape Fear River needed to support the survival of certain species of fish within the river. This minimum regulated flow is a metric for environmental flows. The metric for environmental flows is included in **Table 13**.

Table 13: Performance Metrics

Basin Use	*Performance Metrics*
Water Supply	Minimum and Maximum Daily Withdrawals, Minimum stage within River
Power Generation	Minimum and Maximum Daily Withdrawals, Minimum stage within Reservoir
Recreation	Minimum and Maximum Stage within the Reservoir
Environmental Flows	Minimum Regulatory Flows of 550 cfs ± 50 cfs

6.1.2. Indirect Stakeholder Engagement

Stakeholder engagement was needed to define requirements and acquire baseline data specific to the various basin users within the Buckhorn Creek basin. Due to the difficulty of identifying stakeholders, an indirect stakeholder engagement approach was used for the requirement analysis and to acquire the baseline data. The indirect stakeholder engagement approach used for this research involves acquiring data from indirect sources such as the City of Sanford, NC website, population census data, permit applications for the Shearon Harris Nuclear Power Plant, and other relevant information available on the internet. These data sources provided information about the preferences of the various stakeholders, performance metrics for regulatory purposes, and operation guidelines. Information on the basin uses acquired from these sources are summarized as follows:

Shearon Harris Lake Levels and Intake Elevation:

Data on historical stages within the lake was included in the 2021 National Pollutant Discharge Elimination System (NPDES) permit application for the Shearon Harris Nuclear Power Plant by Duke Energy. The permit application included recorded lake levels from January 2015 to November 2020 (**Table 14**). The data shows that water levels within the Shearon Harris Reservoir range from a high of 221.0 ft NGVD29 (221.6 ft, NAVD88) to a low of 217.5 ft NGVD29 (218.1 ft NAVD88). The baseline operating lake levels for both power generation and recreation are therefore assumed to be between 218.1 ft, NAVD88 to 221.6 ft, NAVD88.

Data included in the NPDES permit also indicated that the bottom elevation at discharge is 175.0 ft, NGVD29 (175.6 ft, NAVD88). The intake elevation was assumed to be 5 feet higher than the bottom elevation at discharge. **Table 14** summarizes the data collected on the Shearon Harris Reservoir. A copy of the NPDES permit application is included in **Appendix A**.

Table 14: Summary of Daily Reservoir Levels (ft, NAVD88) from January 2015 to November 2020

	Case 1: winter Dec-Feb	*Case 2: Spring Mar-May*	*Case 3: Summer Jun-Aug*	*Case 4: Fall Sep-Nov*	*Year Round*
Low Water Level (10th Percentile)	**218.1**	220.4	219.6	218.6	219.4
High Water Level (90th Percentile)	**221.6**	221.5	221.1	221.3	221.4
Median Level (50th Percentile)	220.9	220.9	220.4	220.3	220.6
Bottom elevation at Discharge	175.6	175.6	175.6	175.6	175.6
Intake Elevation	180.6	180.6	180.6	180.6	180.6

Shearon Harris Nuclear Power Plant Water Consumption Rate:

Information provided by Duke Energy about the Shearon Harris Nuclear Power Plant (Duke Energy, 2020) indicates that the plant uses uranium as its fuel and generates electricity through the nuclear fission process. The process of using water in power generation is outlined in the fact sheet from Duke Energy and summarized as follows:

- Water is used to remove heat from the nuclear core with the water temperature reaching 590 degrees Fahrenheit. This happens when water circulates through the nuclear core.

- The heated water flows through tubes within the steam generators while cooler water circulates on the outside of the tubes to generate steam.

- The steam then flows into a turbine and spins large blades attached to a shaft and generator to produce electricity.

- The steam then flows across tubes that contain cool water, which condenses the steam for reuse in the steam generator.

- The heated water is then returned to a cooling tower where it cools down and then returned to the power plant's condenser system.

Although cooling water is recycled through the condenser system, some of the water is lost to the atmosphere (consumed). Due to the sensitive nature of nuclear power plants, specific data on the water consumption at the Shearon Harris Nuclear Power Plant was not available. Data on average water consumption per megawatt-hour of energy generated published by the union of concerned scientists (UCSUSA, 2013) was used to estimate the water requirements for cooling at the Shearon Harris Nuclear Power Plant. Based on the UCSUSA data, about 600 to 800 gallons of water are consumed per megawatt hour of energy produced. Historical energy production data from the United States Energy Information Administration (EIA, 2023) indicate that the Shearon Harris Nuclear Power Plant produces 20,735 MWh of electricity per day.

An analysis of the power generation data by month is shown in **Figure 28**. The data indicates that power generation varies by month with lower generation in the Spring and Fall months and higher generation in the Summer and Winter months. This trend is tied to temperatures and indicates that climate change impacts temperature, which will impact energy production and, hence, water consumption for power generation.

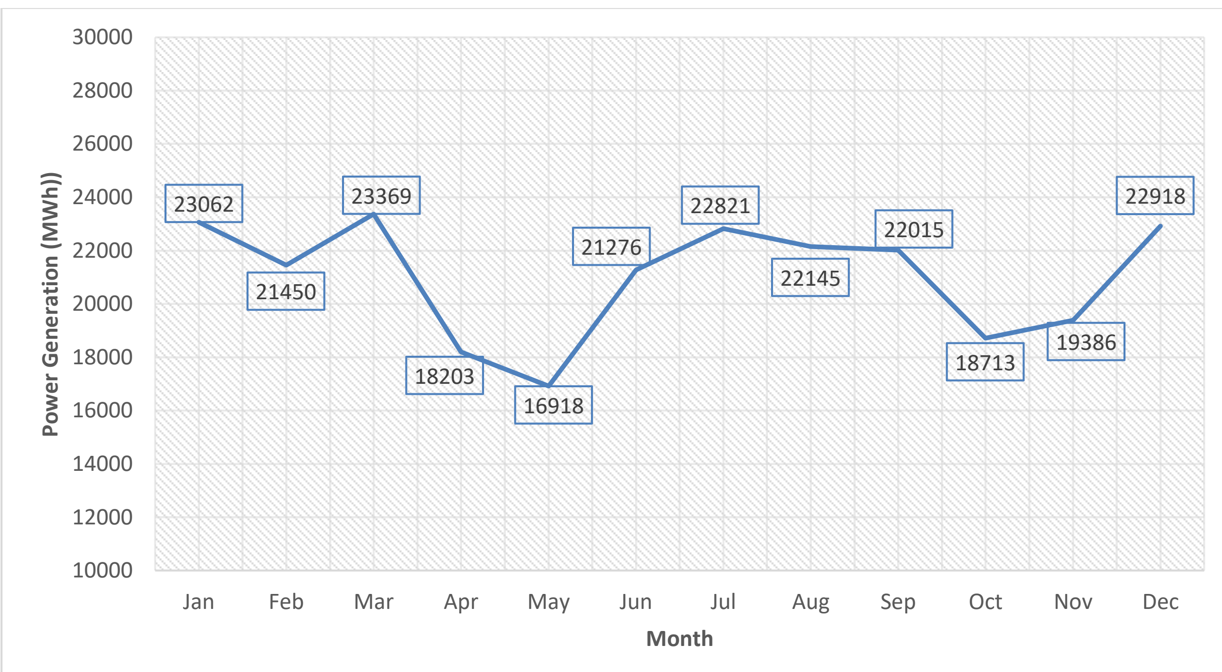


Figure 28: Power Generation at the Shearon Harris Nuclear Power Plant

The estimated water consumption for the Shearon Harris Nuclear Power Plant, assuming 800 gallons of water is consumed per megawatt hour of energy produced, is summarized **Table**

15.

Table 15: Estimated Water Consumption for Power Generation

	Annual Average	Spring-Fall Average	Winter-Summer Average
Water Consumption per Megawatts per hour (gallons)	800	800	800
Plant Capacity (MWh/day)	20,735	19,768	22,279
Plant Water Consumption (gallons per day)	16,588,163	15,814,069	17,823,039

City of Sanford Water Withdrawals and Intake Elevation:

Water withdrawals by the City of Sanford, NC, from the Cape Fear River were not readily available. Water withdrawals were estimated based on the population of the city and data on the average water consumption per person. An additional 20 percent was assumed to account for leakages and industrial uses. The estimated population of the City of Sanford, NC, for 2000, 2010, 2020, and 2022 from the United States Census Bureau (USCB, 2023) is shown in **Table 16**.

According to the United States Environmental Protection Agency, EPA, the average household uses about 300 gallons per day (EPA, 2023). That averages out to about 100 gallons per person per day, assuming each household has three people.

The estimated water supply withdrawals based on the estimated population and average water usage are summarized in **Table 16**. Note that the units of the flows are converted to cubic feet per second (cfs) before being used in the model. I cfs is about 646,317 gpd.

Table 16: City of Sanford, NC Population and Water Withdrawal Trend

Year	*Population*	*Estimated withdrawals without adjustment (gpd)*	*Estimated withdrawals with adjustment (gpd)*
2000	**23,466**	**2,346,600**	**2,815,920**
2010	**28,094**	**2,809,400**	**3,371,280**
2020	**30,261**	**3,026,100**	**3,631,320**
2022	**31,224**	**3,122,400**	**3,746,880**

Data on the intake elevation within the Cape Fear River was not available. The intake elevation was assumed to be 1 foot below the baseflow stage within the Cape Fear River at the location of the intake. This elevation is about **156.5 ft,** NAVD88. The mean monthly gauge height data at the location of the Buckhorn Dam is included in **Appendix A**.

Cape Fear River Environmental Flows:

Jordan Lake is located immediately upstream of the Buckhorn Creek Basin. Jordan Lake is maintained and operated by the United States Army Corps of Engineers (USACE). The USACE is required to maintain a low flow of 600 cfs ± 50 cfs, measured at the USGS gauge 02102500 at Lillington, NC, just downstream of the Buckhorn Creek Basin (NCDENR, 2002). Information about the low-flow requirement is included in **Appendix A**.

The indirect stakeholder engagement process provided data needed to define the requirements for the various basin uses and baseline data for each scenario/baseline year analyzed. These data include the minimum amount of water required to meet the water supply need, the minimum amount of water needed for the power generation need, and the minimum environmental flow requirement.

6.2. Adaptive Management Plan Implementation

This section describes the implementation of the adaptive management framework for the Buckhorn River Basin. The adaptive management framework developed in Chapter 4 (see Figure 6) is repeated here as **Figure 29,** with numbered steps, for easy reference. The indirect stakeholder engagement approach was used to develop data for Steps 1 and 5 in **Figure 29**. To allow for easier validation of the proposed approach, adaptive management is applied in hindcast (Years 2020 through 2022). The adaptive management framework was implemented for scenarios developed based on baseline conditions for the years 2020 and 2022. Per the proposed adaptive management framework, a review of the baseline conditions and updating of the baseline conditions will be needed in 2024 (Step 5 of **Figure 29**).

The following simplifying assumptions were made regarding the hydrologic modeling step, including the rainfall amount used. These assumptions were necessary to overcome computing power limitations:

a. An event-based analysis was performed rather than a continuous simulation covering the period being analyzed. Withdrawals for water supply and energy production are volume-limited, and hence, a continuous simulation will be more appropriate. A continuous hydrologic model simulation covering a duration of a year will, however, take months to complete due to computing power limitations. An event-based simulation was therefore used and assumed to be representative of the average conditions over the period being analyzed. Although the event-based approach allows for easy assessment of climate change impacts in terms of changes in peak rainfall statistics, it does not consider the variability of flows into both the Cape Fear River and the Shearon Harris Reservoir during the period being analyzed. It is expected that the implementation of this framework for the actual design and management of water infrastructure will consider the use of continuous hydrologic model simulations to better assess the temporal variability of flows.

b. The rainfall event with an annual chance of recurrence of 50 percent was used for the event-based analysis. The rainfall estimates are based on the approach described in Chapter 5 and use climate change projections that are calibrated/downscaled based on observed rainfall data. This process allows for accounting for non-stationarity due to climate change.

c. Flow from upstream watersheds into the Cape Fear River portion of the Buckhorn Creek basin was accounted for as baseflow. The baseflow is the Mean Daily Discharge based on USGS stream gauge statistics. A review of the gauges within the Cape Fear River basin indicated that the baseflow is about one cfs per square mile of the upstream basin. The area of the upstream watershed flowing into the Buckhorn Creek basin basins is 3157 mi2. Therefore, the baseflow is estimated to be 3,157 cfs. Upstream flows, however, are regulated by the Jordan Lake and Dam, which has a minimum discharge requirement of 600 cfs. Since the minimum discharge is less than the baseflow, the minimum discharge of 600 cfs was applied at the upstream end of the Cape Fear River portion of the Buckhorn Creek watershed model for all scenarios.

d. The scenarios developed are divided into dry and wet conditions. Dry conditions refer to drought conditions measured in days without rainfall, while the wet seasons refer to seasons with rainfall. The climate change impact assessment approach developed as part of this research relates to rainfall estimates (wet season) and does not account for dry conditions. Assumptions regarding the number of days without rainfall were developed solely to demonstrate the application of the new framework developed in this research. A more detailed assessment of climate change on dry season durations is recommended when applying this approach within multi-use basins.

e. Water supply withdrawal is assumed to be higher during dry conditions as more water will be needed for agriculture, water lawns, etc. In the absence of actual data, a 20-percent increase in water supply is assumed for the purpose of demonstrating the application of the new framework developed in this research.

f. Water consumption for power generation is assumed to be higher during dry conditions. This assumption assumes that dry conditions are directly correlated with higher temperatures. In the absence of actual data, a 20-percent increase in water supply is assumed for the purpose of demonstrating the application of the new framework developed in this research.

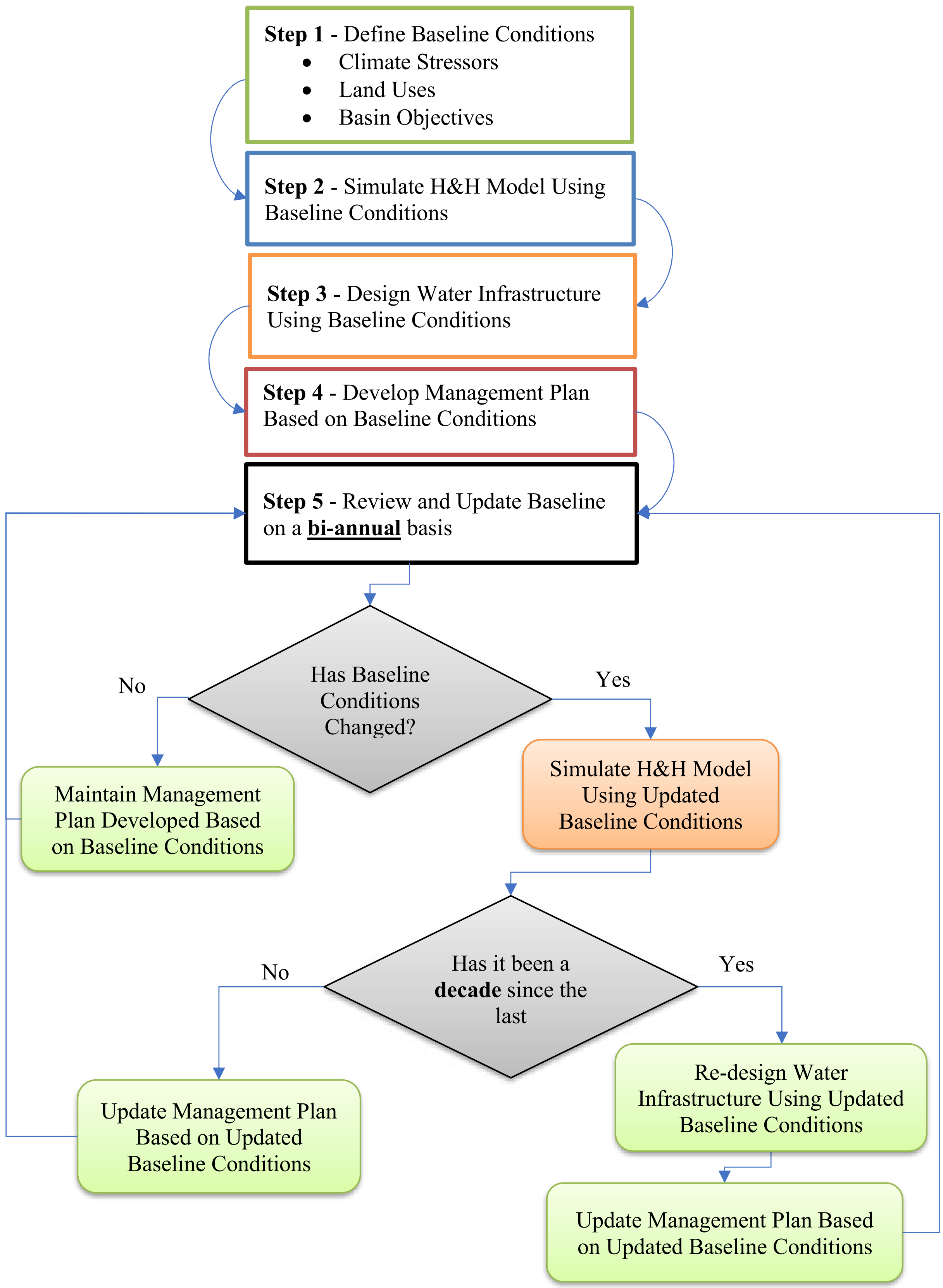


Figure 29: Adaptive Management Framework with Numbered Steps

6.2.1. Scenario 1 – Year 2020

This scenario uses baseline conditions in the year 2020. Per the adaptive management framework (**Figure 29**), the baseline conditions are defined (step 1) and modeled in the H&H model (step 2). The results are then assessed based on the predefined metrics to ascertain whether the system is functioning as intended (step 3). If not, a management plan is developed to mitigate against the shortcomings of the system (step 4). This process is repeated every other year till the tenth year where the water infrastructure is redesigned to meet the system expectations (step 5). These steps are documented for Scenario 1 below.

6.2.1.1. Define Baseline Conditions – Year 2020

The baseline data for the Year 2020 is summarized in **Table 17**. The data summarized in **Table 17** were derived using the indirect stakeholder engagement process. The HEC-SSP analysis to estimate the rainfall value is included in **Appendix B**.

Table 17: Baseline Conditions for Scenario 1.

METRIC / BASELINE CONDITION TYPE	WET CONDITIONS	DRY CONDITIONS
Rainfall (inches/day) / climate stressor	1.85	N/A
Number of days without rainfall / climate stressor	N/A	15
Land use layer year / land uses	2019	2019
Water supply withdrawal (cfs) / basin objective	5.62	6.74
Water usage for power generation (cfs) / basin objective	25.66	30.79

6.2.1.2. H&H Model Simulation with Baseline Conditions - Year 2020

The baseline data for Scenario 1 was modeled as follows:

a. The rainfall amount of 1.85 inches per day was distributed over a 24-hour period in the model for the wet condition simulation as shown in **Figure 30**. No rain was applied for a duration of 15 days for the dry condition simulation.

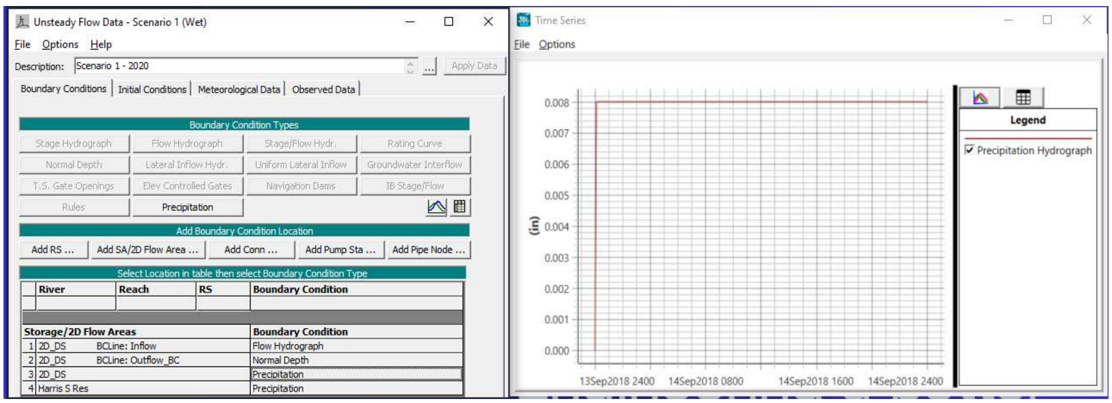


Figure 30: Unsteady Flow Data for Scenario 1

b. The infiltration rates within the model were updated to use the USGS landcover data in 20019. The 2019 landcover data was selected for use from the available options (2001, 2006, 2011, 2016, and 2019) as it was the closest in year to 2020. The Curve Number table in Chapter 5 was maintained for this analysis.

c. The pump feature within HEC-RAS was used to model the withdrawals for water supply. A constant flow of 5.62 cfs (wet conditions) and 6.74 cfs (dry conditions), representing the water supply withdrawals for Scenario 3, was withdrawn from the Cape Fear River. The water supply pump was set to discharge outside of the modeling system. The pump was set to activate once the water levels in the Cape Fear River rose higher than the intake elevation of 156.5 ft, NAVD88. The pump set-up for the water supply withdrawals is shown in **Figure 31**.

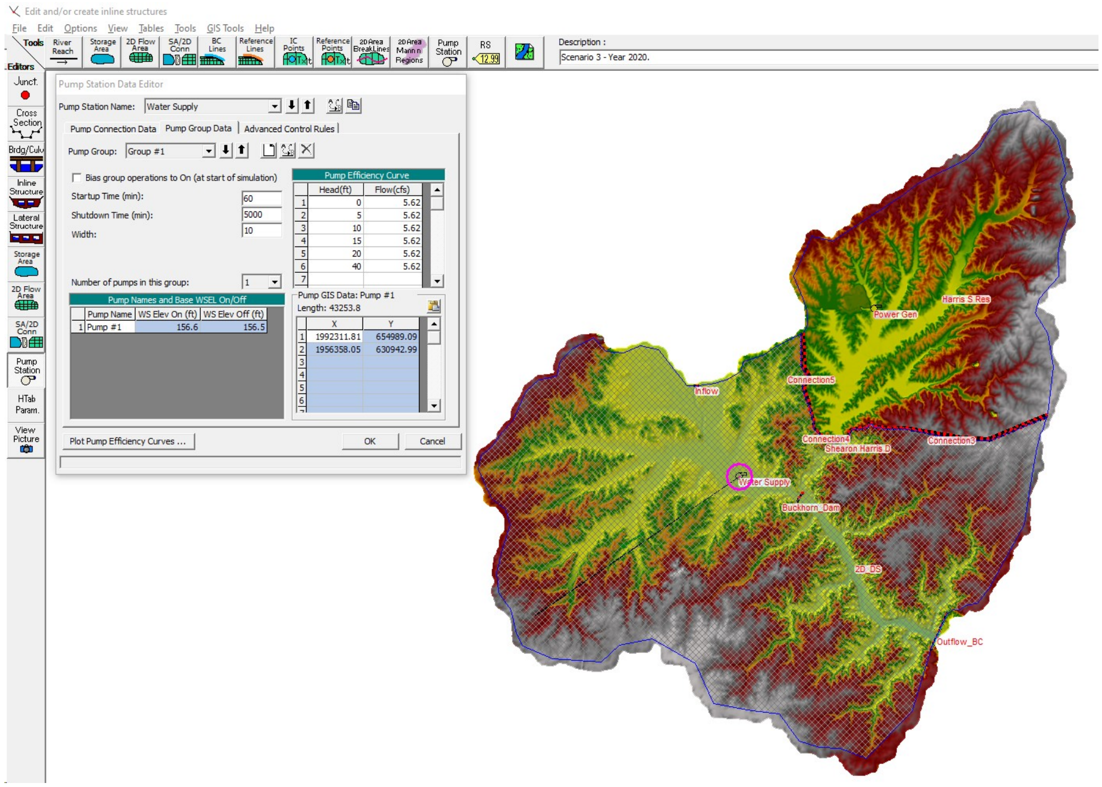


Figure 31: Water Supply Pump Set-up for Scenario 1 (wet conditions)

d. The pump feature within HEC-RAS was also used to model the water consumed for power generation. A constant flow of 25.66 cfs (wet conditions) and 30.79 (dry conditions), representing the water consumed during the power generation process for Scenario 3, was withdrawn from the Shearon Harris Reservoir. The power generation pump was set to discharge outside of the modeling system. The pump was set to activate once the water levels in the Shearon Harris Reservoir rose higher than the intake elevation of 180.5 ft, NAVD88. The pump set-up for the water supply withdrawals is shown in **Figure 32**.

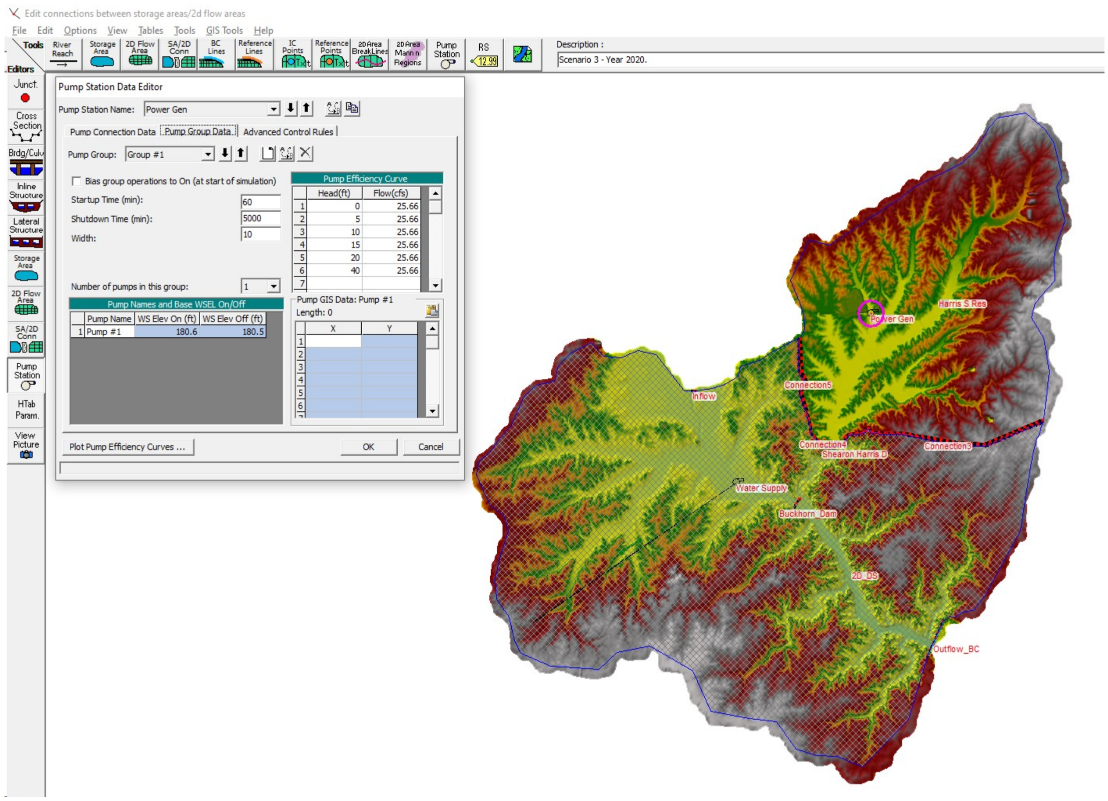


Figure 32: Power Generation Pump Set-up for Scenario 1 (wet conditions)

Two new plans were set up and run for Scenario 1. The results of the simulation are analyzed in the next sub-section.

6.2.1.3. Assessment of System Performance (Step 3) – Year 2020

The results of the H&H model simulation for scenario 1 are summarized in **Table 18** and **Figures 33 and 34**. **Table 18** shows the system performance metrics for each of the basin uses: water supply, power generation, recreation, and environmental flows. **Figure 33** and **Figure 34** show the flow stage and hydrographs at the water supply and power generation intakes, respectively.

For water supply, water cannot be withdrawn if the water level at the intake location falls below the intake elevation. The system is considered to have failed if the water levels in the Cape

Fear River at the intake location falls below the intake elevation.

For power generation, water cannot be withdrawn for cooling if the lake levels fall below the intake elevation for the Shearon Harris Nuclear Power Plant condenser. The system is considered to have failed if the lake levels fall below the intake elevation.

For recreation, the system is considered to have failed if the lake levels fall below the operating levels between 218.1 ft and 221.6 ft, NAVD88.

For environmental flows, the measured flows at USGS gauge 02102500 at Lillington, NC, just downstream of the Buckhorn Creek Basin must be higher than 550 cfs for the system to be considered functional.

Table 18: Scenario 1 Results without Active Management

Basin Use	Metrics	Scenario 1 Results	Pass/Fail
Water Supply (Wet)	Elevation > 156.5 ft	156.5 ft – 173.0 ft	Pass
Water Supply (Dry)		156.5 ft – 174.0 ft	Pass
Power Generation (Wet)	Elevation > 180.5 ft	220.6 ft – 236.9 ft	Pass
Power Generation (Dry)		220.5 ft – 197.5 ft	Pass
Recreation (Wet)	218.1 ft < Elevation > 221.6 ft	220.6 ft – 236.9 ft	Fail
Recreation (Dry)		220.5 ft – 197.5 ft	Fail
Environmental Flows (Wet)	> 550 cfs	9,760 cfs	Pass
Environmental Flows (Dry)		593 cfs	Pass

**Elevations are at intake location and are in ft, NAVD88*

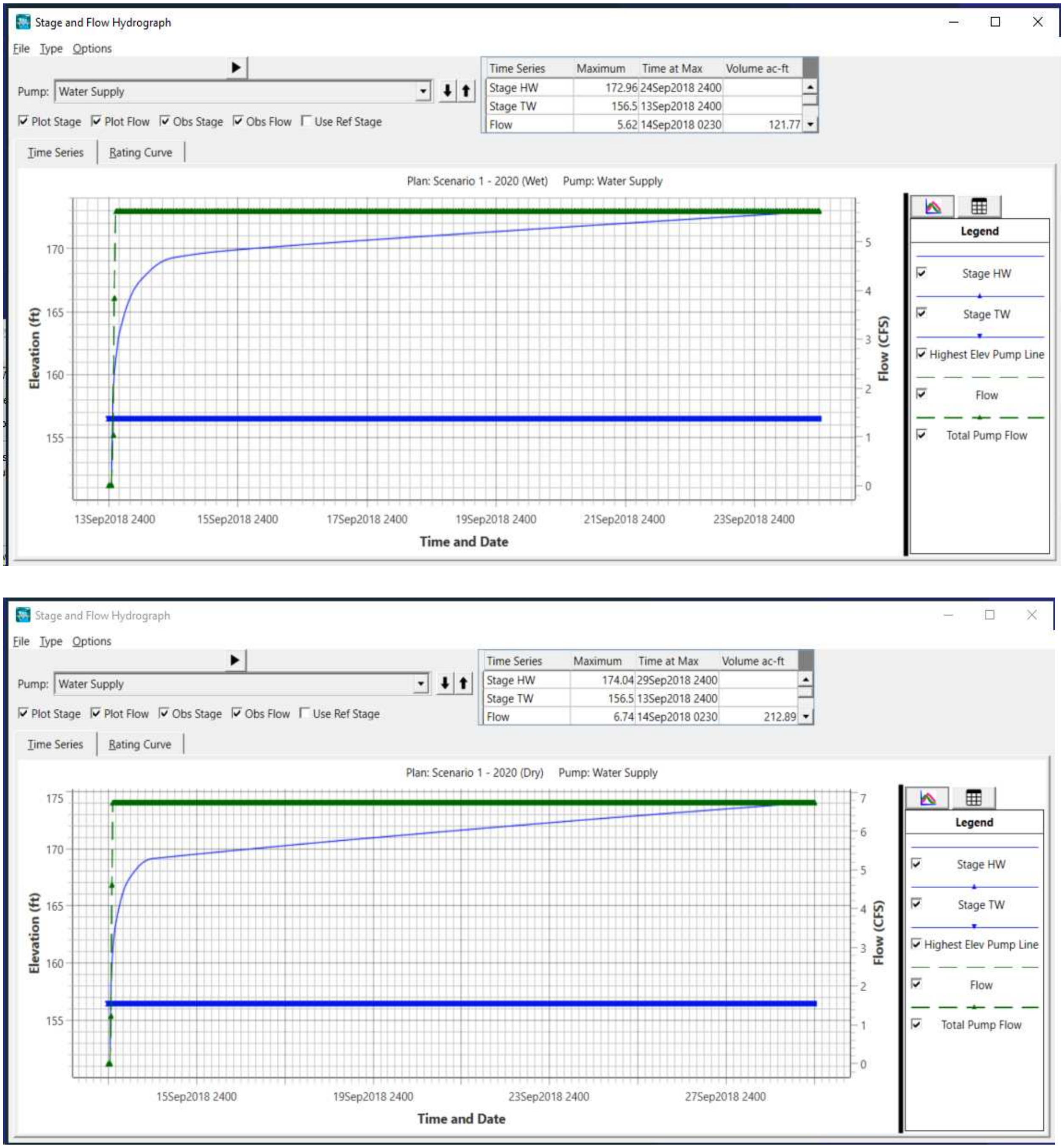
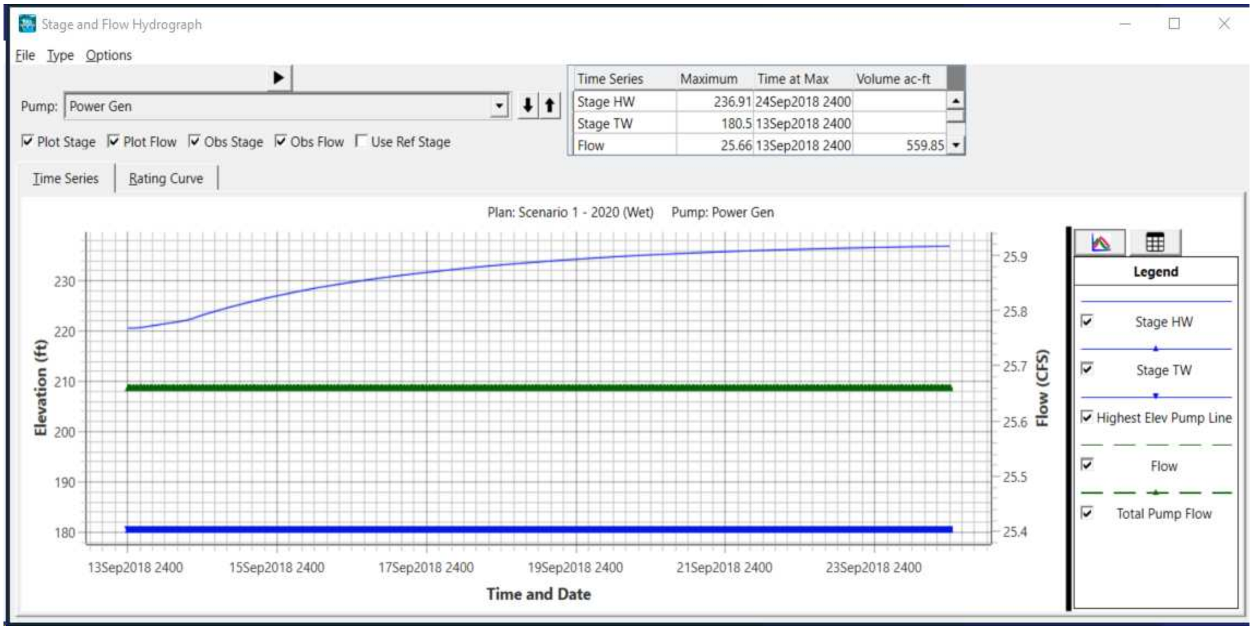


Figure 33: Stage and Hydrograph at Water Supply Intake for Scenario 1 (wet condition-top image; dry condition-bottom image)



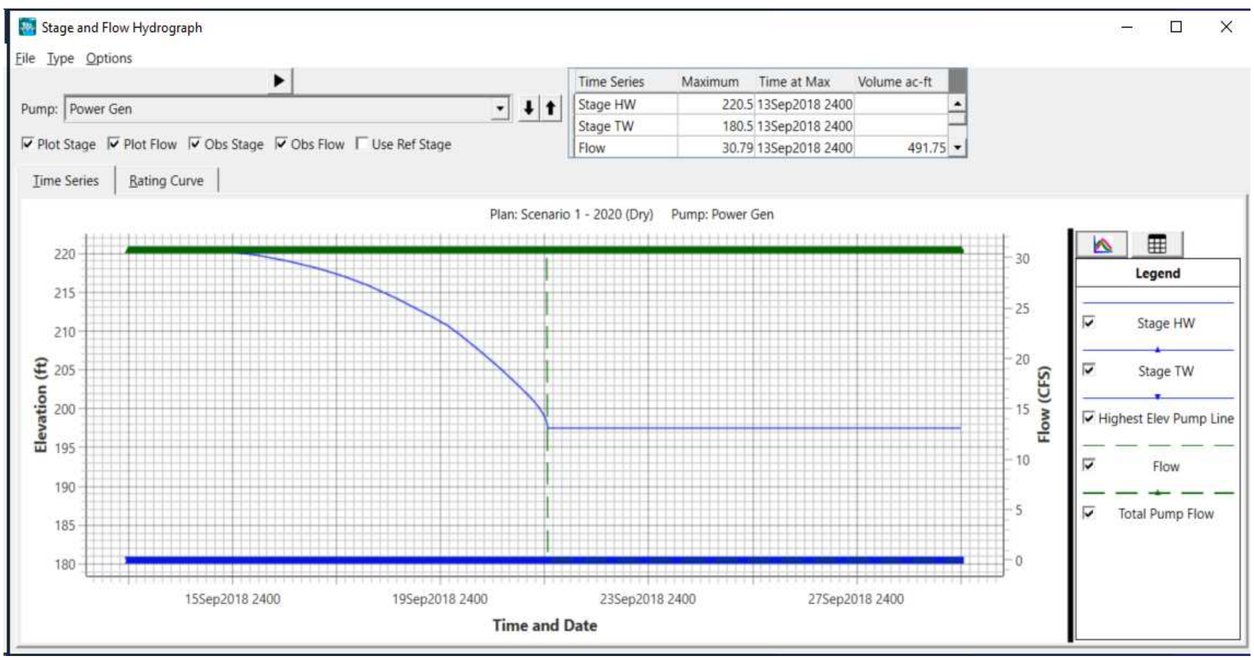


Figure 34: Stage and Flow Hydrograph at Cooling Water Intake for Scenario 1 (wet condition-top image; dry condition-bottom image)

The H&H analysis results for scenario 1 indicate that the water supply, power generation, and environmental flow requirements are being met for both wet and dry conditions. However, the recreational use requirement is not being met. Scenario 1 represents the initial baseline condition.

Per the adaptive management framework, design changes are recommended. The spillway capacity will therefore have to be increased to allow for more flow to be discharged during rain events to maintain water levels within the lake between 218.1 ft, NAVD88 to 221.6 ft, NAVD88 for wet conditions. An active management plan can be relied on if changes to the spillway is not feasible. The active management plan is described in the next sub-section.

6.2.1.4. Management Plan (Step 4) – Year 2020

Based on the results of the H&H simulation for Scenario 1, the Shearon Harris Reservoir water levels will occasionally be too high or too low for recreational use due to climate change. To maintain the recreational use of the reservoir, water levels within the reservoir will have to be reduced prior to rainfall events. Increasing the discharges from the reservoir prior to rain event will not negatively impact other basin uses, including the regulatory flow requirements.

Under dry conditions, recreational activities will have to be limited to activities that are not dependent on lake levels such as fishing. This will require consultation with the basin stakeholders.

Scenario 1 results with active management is shown in **Table 19**. The inclusion of the adaptive management plan provides a response such that all basin uses are functional or basin objectives are adjusted when appropriate to meet the requirements from all stakeholders. Per the adaptive management plan, basin requirements should be updated bi-annually.

Table 19: Scenario 1 Results with Active Management

Basin Use	Metrics	Scenario 1 Results	Pass/Fail
Water Supply (Wet)	Elevation > 156.5 ft	156.5 ft – 173.0 ft	Pass
Water Supply (Dry)		156.5 ft – 174.0 ft	Pass
Power Generation (Wet)	Elevation > 180.5 ft	220.6 ft – 236.9 ft	Pass
Power Generation (Dry)		220.5 ft – 197.5 ft	Pass
Recreation (Wet)	197.5 ft < Elevation > 221.6 ft	220.6 ft – 221.6 ft	Pass
Recreation (Dry)		220.5 ft – 197.5 ft	Pass
Environmental Flows (Wet)	> 550 cfs	9,760 cfs	Pass
Environmental Flows (Dry)		593 cfs	Pass

**Elevations are at intake location and are in ft, NAVD88*

6.2.2. Scenario 2 – Year 2022

This scenario uses baseline conditions in the year 2022. Per the adaptive management framework (**Figure 29**) and like Scenario 1, the baseline conditions are defined (step 1) and modeled in the H&H model (step 2). The results are then assessed based on the predefined metrics to ascertain whether the system is functioning as intended (step 3). If not, a management plan is developed to mitigate against the shortcomings of the system (step 4). This process is repeated every other year till the tenth year where the water infrastructure is redesigned to meet the system expectations (step 5). These steps are documented for scenario 2 below.

6.2.2.1. Define Baseline Conditions (Step 1) – Year 2022

For this scenario, it is assumed to basin uses are updated based on changing needs by the basin stakeholders. The assumed changes in basin uses are:

a. Duke Energy plans to significantly increase energy production due to the opening of a new factory within the Buckhorn Creek basin. This will result in an additional 100 cfs of water consumed from the Shearon Harris Reservoir for cooling.

b. Due to concerns about safety of certain fish species that travel over the Buckhorn Dam, the dam will be removed. This will impact the amount of water available for withdrawal for water supply by the Town of Sanford. It will also impact the water levels at the water supply intake.

c. A new factory has been built in the Town of Sanford and that factory needs 50 cfs of water to operate.

The baseline data for the Year 2022 is summarized in **Table 20**. The HEC-SSP analysis to estimate the rainfall value is included in **Appendix B**.

Table 20: Baseline Conditions for Scenario 2.

METRIC / BASELINE CONDITION TYPE	WET CONDITIONS	DRY CONDITIONS
Rainfall (inches/day) / climate stressor	1.89	N/A
Number of days without Rainfall / climate stressor	N/A	16
Land use layer year / land uses	2019	2019
Water supply withdrawal (cfs) / basin objective	55.80	56.96
Water usage for power generation (cfs) / basin objective	125.66	130.79

6.2.2.2. H&H Model Simulation with Baseline Conditions (Step 2) - Year 2022

The baseline data for Scenario 2 was modeled as follows:

a. The rainfall amount of 1.89 inches per day was distributed over a 24-hour period in the model for the wet condition simulation as shown in **Figure 35**. No rain was applied for a duration of 16 days for the dry condition simulation.

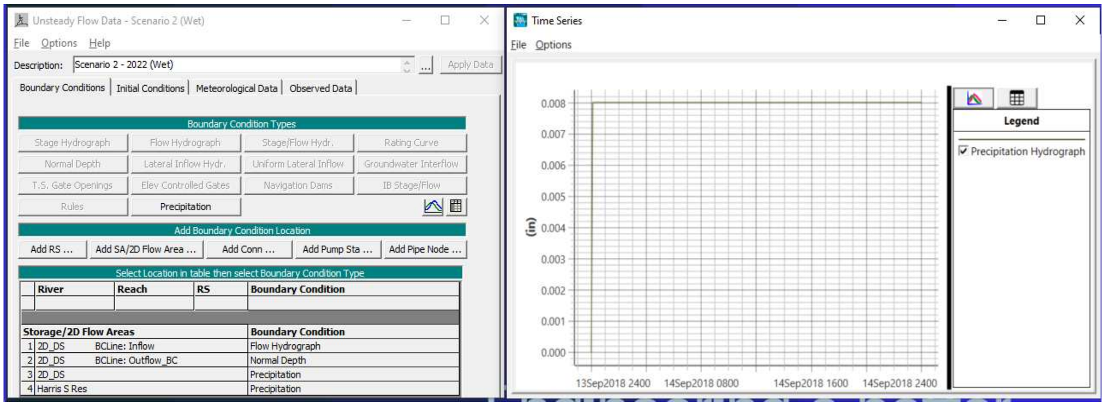


Figure 35: Unsteady Flow Data for Scenario 2 (wet conditions)

b. The infiltration rates within the model were updated to use the USGS landcover data in 20019. The 2019 landcover data was selected for use from the available options (2001, 2006, 2011, 2016, and 2019) as it was the closest in year to 2022. The Curve Number table in Chapter 5 was maintained for this analysis.

c. The pump feature within HEC-RAS was used to model the withdrawals for water supply. A constant flow of 55.80 cfs (wet conditions) and 56.96 cfs (dry conditions), representing the water supply withdrawals for Scenario 2, was withdrawn from the Cape Fear River. The water supply pump was set to discharge outside of the modeling system. The pump was set to activate once the water levels in the Cape Fear River rose higher than the intake elevation of 156.5 ft, NAVD88. The pump set-up for the water supply withdrawals is shown in **Figure 36**.

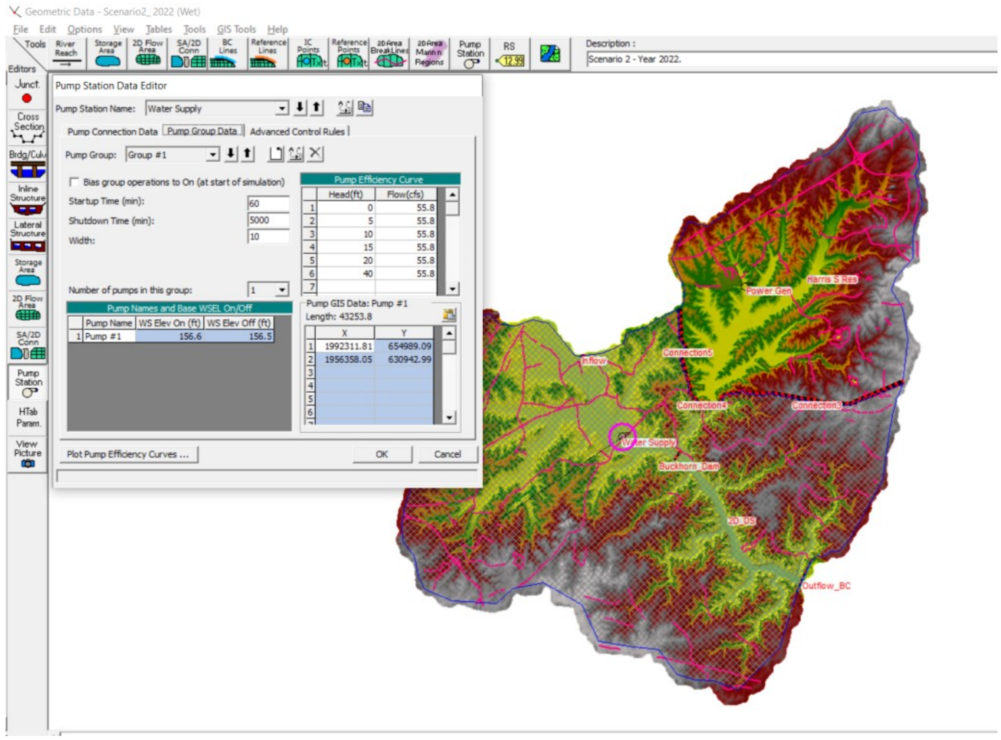


Figure 36: Water Supply Pump Set-up for Scenario 2 (wet conditions)

d. The pump feature within HEC-RAS was also used to model the water consumed for power generation. A constant flow of 125.66 cfs (wet conditions) and 130.79 (dry conditions), representing the water consumed during the power generation process for Scenario 2, was withdrawn from the Shearon Harris Reservoir. The power generation pump was set to discharge outside of the modeling system. The pump was set to activate once the water levels in the Shearon Harris Reservoir rose higher than the intake elevation of 180.5 ft, NAVD88. The pump set-up for the water supply withdrawals is shown in **Figure 37**.

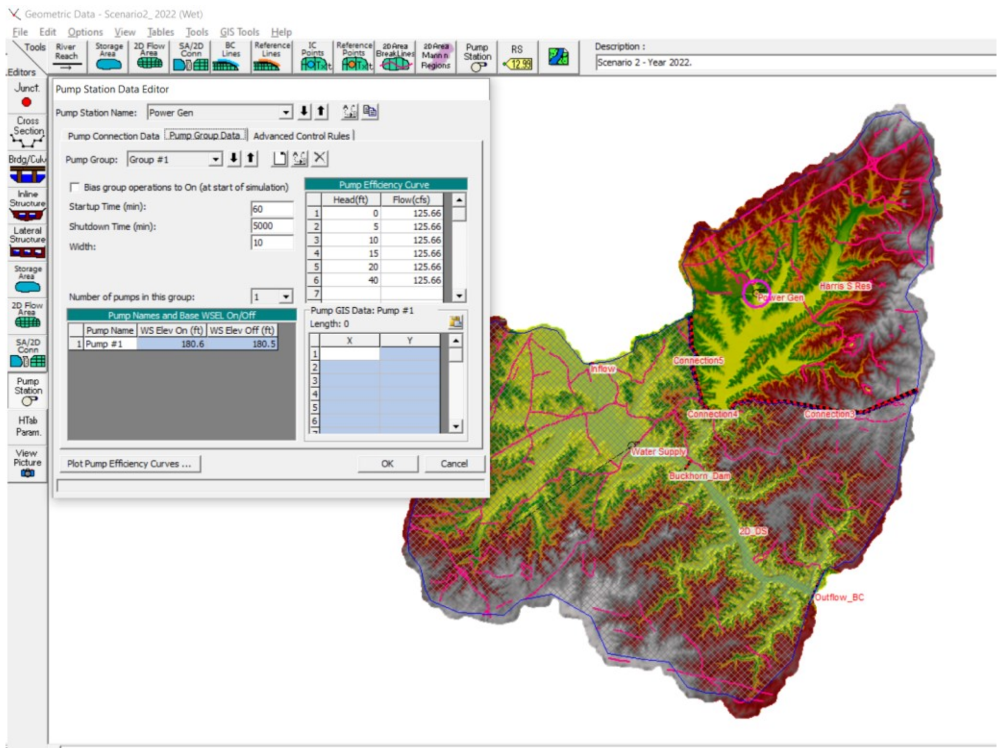


Figure 37: Power Generation Pump Set-up for Scenario 2 (wet conditions)

Two new plans set-up and run for Scenario 2. The results of the simulation are analyzed in the next sub-section.

6.2.2.3. Assessment of System Performance (Step 3) – Year 2022

The results of the H&H model simulation for scenario 2 are summarized in **Table 21** and **Figures 38 and 39**. **Table 21** shows the system performance metrics for each of the basin uses: water supply, power generation, recreation, and environmental flows. **Figure 38** and **Figure 39** show the flow stage and hydrographs at the water supply and power generation intakes, respectively.

The metrics for assessing the performance of the system is the same as for Scenarios 1. For water supply, water cannot be withdrawn if the water level at the intake location falls below the intake elevation. The system is considered to have failed if the water levels in the Cape Fear River at the intake location falls below the intake elevation.

For power generation, water cannot be withdrawn for cooling if the lake levels fall below the intake elevation for the Shearon Harris Nuclear Power Plant condenser. The system is considered to have failed if the lake levels fall below the intake elevation.

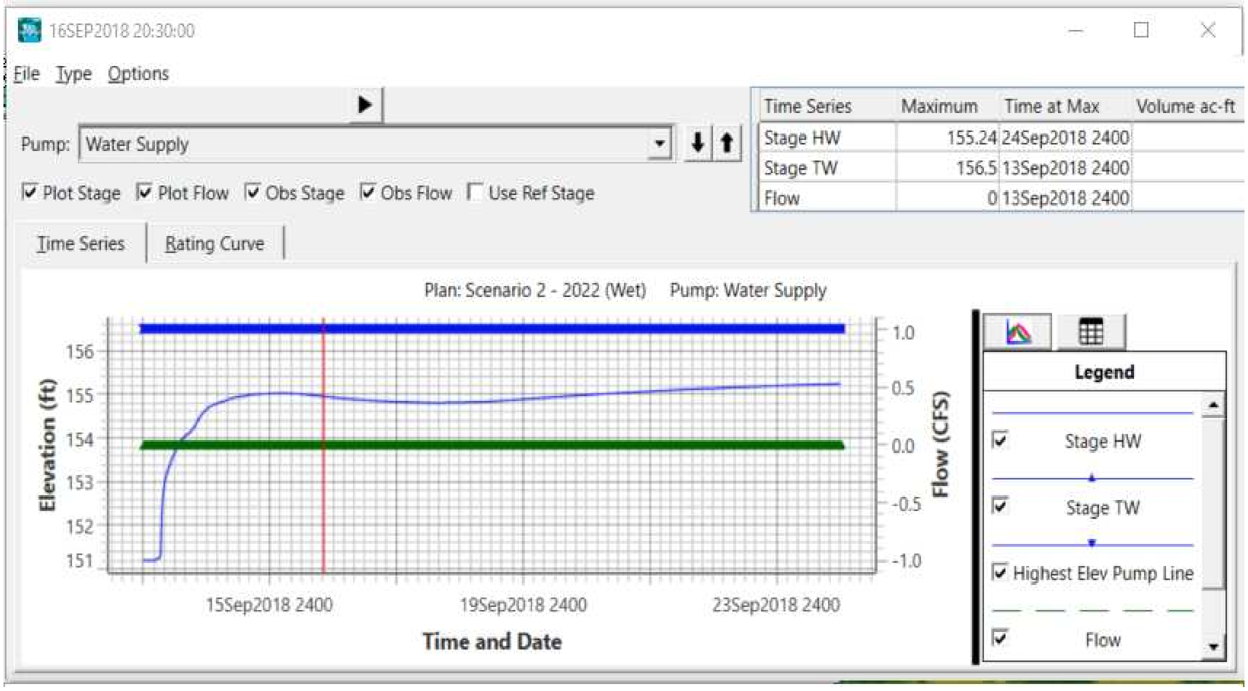
For recreation, the system is considered to have failed if the lake levels fall below the operating levels between 218.1 ft and 221.6 ft, NAVD88.

For environmental flows, the measured flows at USGS gauge 02102500 at Lillington, NC, just downstream of the Buckhorn Creek Basin must be higher than 550 cfs for the system to be considered functional.

Table 21: Scenario 2 Results

Basin Use	Metrics	Scenario 1 Results	Pass/Fail
Water Supply (Wet)	Elevation > 156.5 ft	155.0 ft – 155.2 ft	Fail
Water Supply (Dry)		151.2ft – 154.7 ft	Fail
Power Generation (Wet)	Elevation > 180.5 ft	220.6 ft – 236.3 ft	Pass
Power Generation (Dry)		220.5 ft – 197.5 ft	Pass
Recreation (Wet)	218.1 ft < Elevation > 221.6 ft	220.6 ft – 236.3 ft	Fail
Recreation (Dry)		220.5 ft – 197.5 ft	Fail
Environmental Flows (Wet)	> 550 cfs	9,780 cfs	Pass
Environmental Flows (Dry)		600 cfs	Pass

**Elevations are at intake location and are in ft, NAVD88*



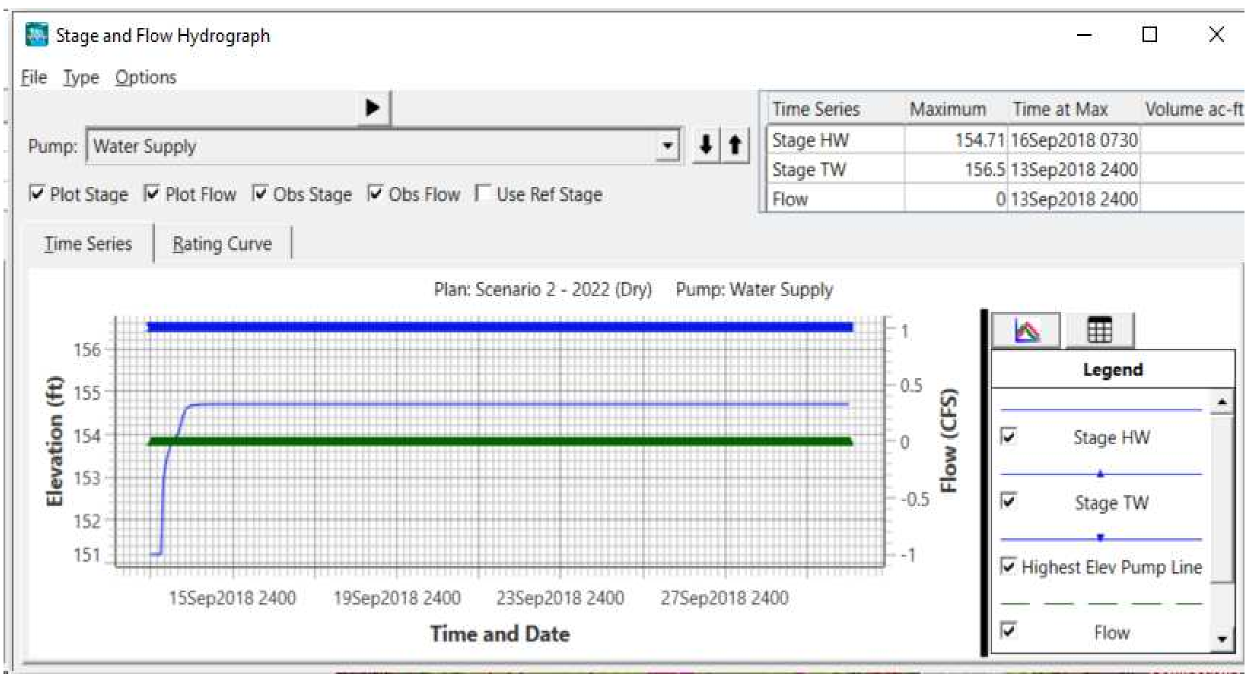
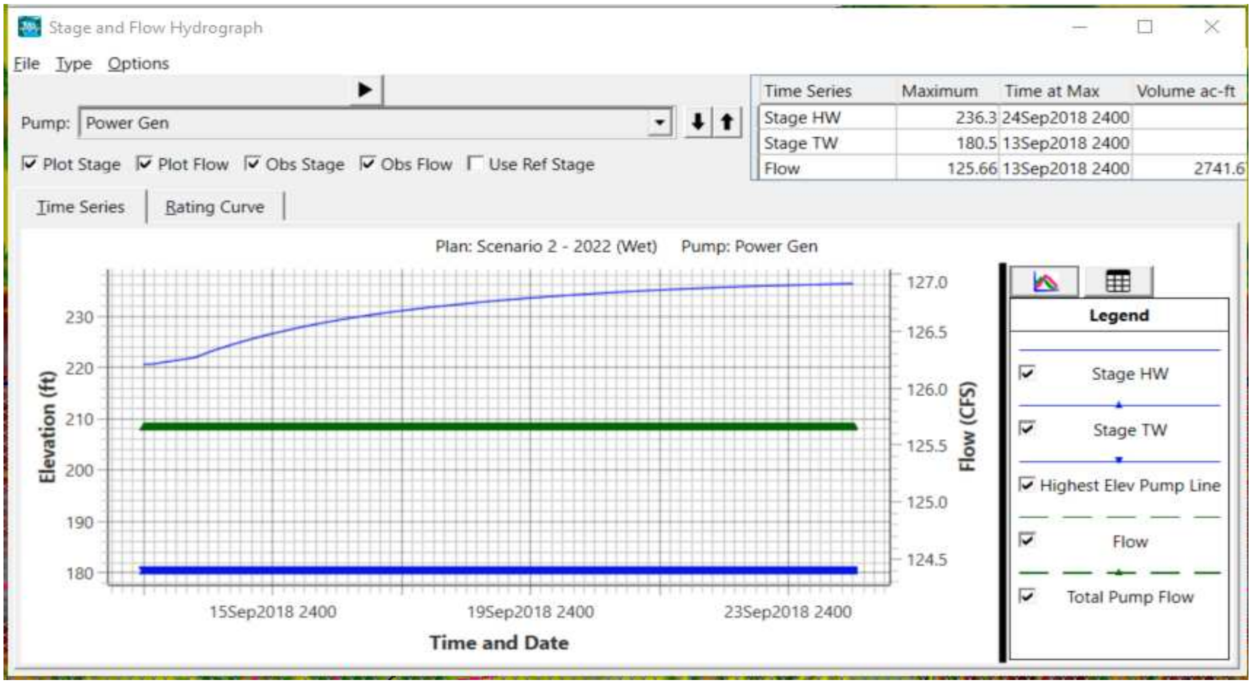


Figure 38: Stage and Hydrograph at Water Supply Intake for Scenario 2 (wet condition-top image; dry condition-bottom image)



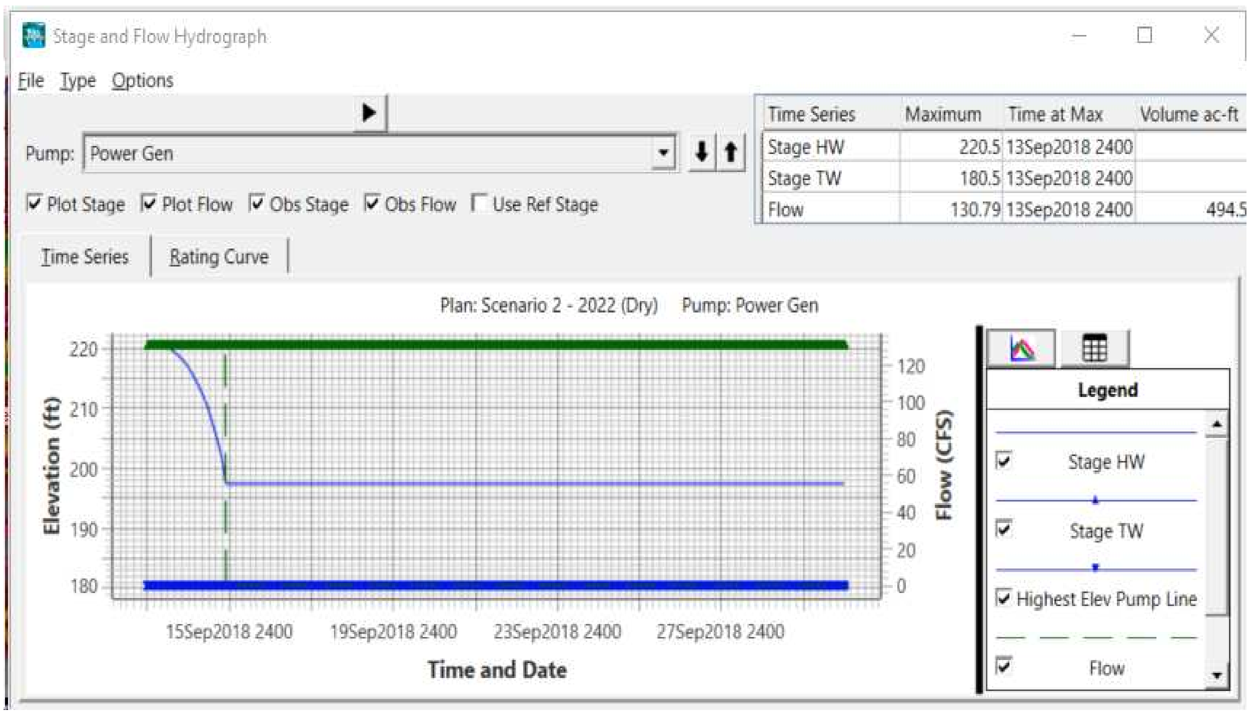


Figure 39: Stage and Flow Hydrograph at Cooling Water Intake for Scenario 2 (wet condition-top image; dry condition-bottom image)

The H&H analysis results for scenario 2 indicate that the requirements for power generation, and environmental flows are met for both the dry and wet conditions. However, the requirements for water supply and recreation are not met. For water supply, the removal of the Buckhorn Dam results in loss of the impoundment behind the dam leading to the water levels in Cape Fear falling below the water supply intake elevation of 156.5 ft, NAVD88. For recreational use, lake levels rise to levels too high under the wet condition and fall too low under the dry condition for recreational use.

An active management is required to ensure that all basin use requirements are met for Scenario 2. The active management plan for Scenario 2 is described in **Section 6.2.2.4**.

6.2.2.4. Management Plan (Step 4) – Year 2022

Based on the results of the H&H simulation for Scenario 2, the Shearon Harris Reservoir water levels will occasionally be too high for recreational use due to higher rainfall amounts due to climate change. To maintain the recreational use of the reservoir, water levels within the reservoir will have to be reduced prior to rainfall events. Increasing the discharges from the reservoir prior to rain event will not negatively impact other basin uses, including the regulatory flow requirements.

Under dry conditions, recreational activities will have to be limited to activities that are not dependent on lake levels such as fishing. This will require consultation with the basin stakeholders.

Failure of the water supply requirement is mainly due to the removal of the Buckhorn Dam. The results of the H&H simulation indicates that the water levels fall below the water supply intake elevation by a maximum of 4.3 ft under the dry conditions scenario. This can be averted by coordination between Duke Energy and the Town of Sanford to maintain a minimal impoundment at the location of the Buckhorn Dam such that fish can safely pass without impacting the water supply needs of the Town of Sanford. The management plan will entail regular coordination between Duke Energy and the Town of Sanford during the planning for the removal of the dam.

Additional coordination between the Town of Sanford and the US Army Corps of Engineers, who operates the Jordan Lake levels, to release additional flows from the Jordan Lake to offset the increased withdrawals by the City of Sanford.

Scenario 2 results with active management is shown in **Table 22**. Having an active management plan ensures that all basin uses are functional or basin objectives are adjusted when appropriate to meet the requirements from all stakeholders. Per the adaptive management plan, basin requirements should be updated bi-annually.

Table 22: Scenario 2 Results with Active Management

Basin Use	**Metrics**	**Scenario 2 Results**	**Pass/Fail**
Water Supply (Wet)	Elevation > 156.5 ft	156.5 ft – 173.0 ft	Pass
Water Supply (Dry)		156.5 ft – 174.3 ft	Pass
Power Generation (Wet)	Elevation > 180.5 ft	220.6 ft – 236.4 ft	Pass
Power Generation (Dry)		220.5 ft – 197.5 ft	Pass
Recreation (Wet)	197.5 ft < Elevation > 221.6 ft	220.6 ft – 221.6 ft	Pass
Recreation (Dry)		220.5 ft – 197.5 ft	Pass
Environmental Flows (Wet)	> 550 cfs	9,780 cfs	Pass
Environmental Flows (Dry)		600 cfs	Pass

**Elevations are at intake location and are in ft, NAVD88*

6.3. Comparison of New Approach Results with Traditional Approach Results

6.3.1. Traditional Approach Results

As noted in Chapters 1 through 3, the traditional approach for designing and managing water infrastructure does not account for non-stationarity due to climate and only accounts for the objectives of the primary water infrastructure. To compare the performance of the new approach developed as part of this research to that from the traditional approach, the H&H model was modeled using baseline conditions representative of the traditional approach and the results were compared to that reported in Section 6.2.

The following assumptions were made in developing the baseline conditions for the traditional approach:

1. The primary objective for the Buckhorn Creek basin is assumed to be water supply.
2. The design year for the water supply infrastructure is assumed to be 2020.
3. Land cover conditions in 2019 were assumed to have been used for the design of the water supply infrastructure.
4. The design life for the water supply infrastructure is assumed to be 50 years.
5. Design for the water supply infrastructure is assumed to use rainfall estimates in the year 2020.
6. Population estimates used for the designing the water supply infrastructure is assumed to be based on projections for Year 2070.

The baseline conditions for the traditional approach are summarized in **Table 23**.

Table 23: Baseline Conditions for Traditional Approach.

METRIC / BASELINE CONDITION TYPE	WET CONDITIONS	DRY CONDITIONS
Rainfall (inches/day) / climate stressor	1.85	N/A
Number of days without Rainfall / climate stressor	N/A	15
Land use layer year / land uses	2019	2019
Water supply withdrawal (cfs) / basin objective	10.87	13.04
Water usage for power generation (cfs) / basin objective	25.66	30.79

Modeling results based on the baseline conditions for the traditional approach are summarized in **Table 24**. The results indicate that the recreational needs of the basin will not be met using the traditional approach during scenario 1 (the base year of 2020). This is because of increases in rainfall amounts due to climate change which leads to high lake levels, and the fact that the traditional approach only focuses on the primary objective of water supply, without consideration for the other basin needs. The power supply and regulatory flows needs are only met because those requirements do not exert a huge demand on the basin resources. Those requirements are likely to also fail if more water is needed for power generation cooling and aquatic life.

The traditional approach fails for all basin needs for scenario 2 (Year 2022). This is because the basin needs change in 2022 and the traditional approach is inadequate to handle such changes.

Table 24: Traditional Approach Results

Basin Use	Metrics	Traditional Approach Results 2020	2020 Results Pass/Fail	2022 Results Pass/Fail
Water Supply (Wet)	Elevation > 156.5 ft	156.5 ft – 175.6 ft	Pass	Fail
Water Supply (Dry)		156.5 ft – 175.6 ft	Pass	Fail
Power Generation (Wet)	Elevation > 180.5 ft	220.5 ft – 237.5.0 ft	Pass	Pass
Power Generation (Dry)		220.5 ft – 197.5 ft	Pass	Fail
Recreation (Wet)	218.1 ft < Elevation > 221.6 ft	220.5 ft – 237.5 ft	Fail	Fail
Recreation (Dry)		220.5 ft – 197.5 ft	Fail	Fail
Environmental Flows (Wet)	> 550 cfs	10,980 cfs	Pass	Pass
Environmental Flows (Dry)		587 cfs	Pass	Fail

**Elevations are at intake location and are in ft, NAVD88*

6.3.2. Comparison of Results

A comparison of the results based on the traditional approach and the new approach from this research work is shown in **Table 25**. The results indicate that, unlike the traditional approach, the new approach makes it possible to meet the basin requirements even under uncertain and nonstationary conditions such as changing basin uses, climate, basin uses, and land use.

Table 25: Comparison of Results from Traditional and New Approach

Basin Use	Wet / Dry Conditions	Traditional Approach		New Approach	
		Scenario 1 (Year 2020)	Scenario 2 (Year 2022)	Scenario 1 (Year 2020)	Scenario 2 (Year 2022)
Water Supply	Wet Conditions	Pass	Fail	Pass	Pass
	Dry Conditions	Pass	Fail	Pass	Pass
Power Generation	Wet Conditions	Pass	Pass	Pass	Pass
	Dry Conditions	Pass	Fail	Pass	Pass
Recreation	Wet Conditions	Fail	Fail	Pass	Pass
	Dry Conditions	Fail	Fail	Pass	Pass
Environmental Flows	Wet Conditions	Pass	Pass	Pass	Pass
	Dry Conditions	Pass	Fail	Pass	Pass

6.3.3. Discussions

The results shown in this chapter demonstrate the need for the new approach and shows the benefits of applying the new approach in multi-use basins. The results indicate that the recreational needs of the basin will not be met under scenario 1 (the base year of 2020) and all basin needs will not be met under scenario 2, when the traditional approach is used. This is because of increases in rainfall amounts due to climate change which leads to high lake levels, and the fact that the traditional approach only focuses on the primary objective of water supply, without consideration for the other basin needs. The power supply and regulatory flows needs are only met because those requirements do not exert a huge demand on the basin resources. Those requirements are likely to also fail if more water is needed for power generation cooling and aquatic life.

The traditional approach fails for all basin needs for scenario 2 (Year 2022) because the basin needs change in 2022 and the traditional approach is inadequate to handle such changes.

However, using the new approach makes it possible to meet the basin requirements even under uncertain and nonstationary conditions such as changing climate, basin uses, and land use.

The use of an adaptive management framework results in more accurate data for decision making since the climate projections being used for the design and management of the water infrastructure are reviewed and updated bi-annually. It also provides an opportunity to tailor the design and management of water infrastructure to changes to basin use requirements, and land uses.

It is worth pointing out that the new approach can be used in the design and management of both existing and new water infrastructure. For the pilot basin, the water infrastructure already existed. However, the process demonstrated will be the same if the infrastructure did not already exist.

As noted in Chapter 2, the success of the approach depends on its ability to cost-effectively use climate change projections, its applicability to all basins and projects, irrespective of geographic location, size, or uses and its ability to independently duplicate the results produced by the approach.

As demonstrated in its application to the Buckhorn Creek basin, this new approach for designing and managing water infrastructure in multi-use basins is very cost effective when compared to the traditional approach. The effort required for initial modeling effort and design is similar for both the new and traditional approaches. The effort required for the bi-annual updates are minimal since the bi-annual updates builds on the initial data and H&H model. Bi-annual updates can be completed in a matter of hours but provide increased certainty for decision making which can lead to considerable financial savings for stakeholders.

The universal applicability of the new approach to all basins and projects, irrespective of geographic location, size, or uses is also demonstrated in its application to the Buckhorn Creek basin. Although basin uses and data may change from location to location, the underlying principles for designing and managing water infrastructure in multi-used basins remain the same.

The new approach has limited subjective components and can therefore be duplicated by others so long as all assumptions made are well documented. This is evidenced by its application to the Buckhorn Creek basin.

CHAPTER 7: RESEARCH CONTRIBUTIONS

The objective of the research is to develop a demonstrably improved approach for designing and managing water infrastructure that uses quantifiable hydrological estimates of the future climate and accounts for multiple objectives from multiple stakeholders. Research and practical contributions from this work include the following papers, hydrologic and hydraulic models, tools and new approaches that can be applied directly in helping stakeholders within multi-use basins better account for climate change and competing basin uses:

1. Publication on "*Accounting for Climate Change in Water Infrastructure Design: Evaluating Approaches and Recommending a Hybrid Framework*" in the Journal of Water and Climate Change (Hunu et al., 2023).

2. An Adaptive Management Framework for accounting for nonstationarity due to climate change, changes in land use due to urbanization, and basin uses within multi-use basins.

3. Poster on "*Systems Engineering Views on Adaptive Management Framework for Water Infrastructure"*. Submitted for presentation during the 2024 Conference on Systems Engineering Research in Tucson, Arizona.

4. A hydrologic and hydraulic model of the Buckhorn Creek basin that can be used in testing alternative approaches for accounting for climate change in hydrologic design and management of the water supply, power generation, and recreational uses of the basin.

5. An Indirect Stakeholder Engagement Approach that can be applied to future analysis.

6. This Dissertation

7. A demonstrably improved and practical approach for designing and managing water infrastructure that uses quantifiable hydrological estimates of the future climate and accounts for multiple objectives from multiple stakeholders.

8. Contributions to the Research and Development by the U.S. Department of Energy (DOE) in the form of responses to their April 2022 request for information (RFI) on how the hydropower community may leverage state-of-the-art climate change science to inform hydropower operation and resource planning. This RFI is directly related to Research Question 1. Findings from this research work was submitted in response to the RFI. The responses included information about the risks posed by climate change on hydropower facilities, the meteorologic and hydrologic variables my company is using to support water infrastructure planning, data and research needs that could be beneficial to the water industry. My responses to the RFI are included as **Appendix C**.

Future contributions

1. Peer reviewed journal paper presenting the systems engineering view on adaptive management framework. Target Journal, *Systems Engineering*
2. Peer reviewed journal paper on the application of the hybrid framework and indirect stakeholder engagement and modeling exercises developed for the Buckhorn Creek Basin.

CHAPTER 8: CONCLUSIONS

8.1. Dissertation Summary

8.1.1. Chapter Summaries

Chapter 1 introduces the problem statement. As noted in Chapter 1, although the earth's climate is changing (IPCC, 2014), traditional hydrologic design of water infrastructure assumes that the climate is stationary and hence historic data reflect future conditions. Additionally, design of water infrastructure to meet a particular need is often considered a single objective optimization problem and done without considering other basin constraints and competing watershed uses which may include recreation, hydropower generation, flood control, environmental flows, and water supply. The single-objective design approach routinely fails to adequately address the challenges of complex systems such as multi-use river basins that require an understanding of the linkages between the various uses and stakeholders (Anderson, et.al., 2008). There is therefore a need for a new, holistic approach for designing and managing water infrastructure that accounts for nonstationarity due to climate change and requirements from all basin uses.

Chapter 1 also lays out the research approach which includes identifying the systems engineering problem, performing extensive literature review on the current state of practice, collecting, and analyzing data, developing an analysis tool and framework that can be used to test various hypothesis to develop the required approach for designing and managing water infrastructure, and finally testing and validating the new approach.

Chapter 2 identifies the research questions and tasks needed resolve the problem statement. Four research questions were identified. These are (1) What are the shortcomings of the current approaches for accounting for nonstationarity in the design and management of water infrastructure? (2) What are the current approaches for accounting for multi-use basin objectives; (3) How can the deficiencies of the existing approaches for accounting for nonstationarity and multiple basin objectives be addressed? and (4) How does the new approach that accounts for nonstationarity and multiple objectives compare to the traditional approach?

The main tasks identified to be performed include (1) Review of existing literature and case studies; (2) conduct semi-structured interviews with expert water professionals and research advisors to identify possible solutions to accounting for nonstationarity including adaptive design and management strategies; (3) Identify the sources of uncertainty in the design and management of water infrastructure in multi-use basins and the baseline conditions for the all the identified sources of uncertainty; (4) Acquire climate change, hydrologic and hydraulic data, and build a hydrologic and hydraulic model for a case study basin; (5) Develop and adaptive management framework (approach) to allow for future updates to design and management based on increased forecast accuracy in the future and changing basin objectives; and (6) Compare and contrast the new approach to the traditional approach and document findings and recommendations.

Chapter 3 identifies the shortcomings of the current approaches for accounting for nonstationarity in the design and management of water infrastructure and recommends an approach to address the deficiencies. Five approaches for accounting for climate change were identified in Chapter 3. These are: adaptive management, inverse climate change impact method, machine learning, updated flood frequency analysis, and soft computing approaches. Except for the soft computing approaches, all these methods rely on climate projections from GCMs and downscaling techniques. All five approaches recognize that there is uncertainty in climate data available for decision making due to the uncertainty in the GCM outputs, the downscaling methods, among others.

The flood frequency analysis approach may likely be the most applicable to water infrastructure design as it may be, among those reviewed, the least disruptive in terms of standard hydrological analysis methods, is cost-effective and adaptable to most basins. However, adaptive management approaches may be best suited for reductions in uncertainty since they provide for opportunities to constantly adjust decisions based on improved climate change data. A combination of flood frequency and adaptive management approaches is, therefore, recommended as an effective and practical way of accounting for climate change in the design and management of water infrastructure.

In **Chapter 4**, an effective and practical approach for accounting for multi-use basin objectives in the design and management of water infrastructure was developed in response to Research Questions 2 and 3. The approach is an adaptive management framework that defines and maintains baseline objectives of existing basin users while designing the primary water infrastructure, in a manner that accounts for nonstationarity and uncertainty. The adaptive management approach allows for regular review and refinement of the application of climate data and adjustments to basin objectives, thereby reducing uncertainty within the data needed for decision-making. The adaptive management framework involves the following steps: (1) Defining baseline conditions, (2) simulating H&H model using the baseline conditions, (3) assessing the performance of the system based on the baseline conditions and making design changes as necessary, (4) developing an active management plan to mitigate and failures identified in step 3, and (3) reviewing and updating baseline conditions and repeating steps 2, 3, and 4.

Chapter 5 describes the development of the development of the H&H data and model. The H&H data includes an approach for accounting for climate change projections and implements the recommendations from Chapter 3.

In **Chapter 6,** the new approach that combines the adaptive management framework, the H&H model and the climate data is implemented for a pilot basin to demonstrate the implementation of the new approach and the results compared to those from using the traditional approach. Chapter 6 demonstrates that the new approach:

1. Provides a cost-effective way to use climate change projections.
2. Is applicable to all basins and projects, irrespective of geographic location, size, or basin uses.
3. The results from the pilot basin can be duplicated by others as the approach has minimal subjective components.

Research contributions from this dissertation are listed in **Chapter 7**.

8.2. Future Work

The following future work are recommended to address some of the limitations of this research:

3. It is recommended that the approach be tested on other pilot basins located within other basins.
4. The approach should be implemented using a continuous model simulation to capture temporal variations within the hydrological system.
5. A more detailed assessment of the effects of climate change impacts on temperature on basins should be done and incorporated into the framework.

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APPENDIX A: DATA FROM INDIRECT STAKEHOLDER ENGAGEMENT

CAPE FEAR RIVER DATA

UNITED STATES GEOLOGICAL SURVEY (USGS) DATA

Water-Data Report 2011

02102500 CAPE FEAR RIVER AT LILLINGTON, NC

Cape Fear Basin
Upper Cape Fear Subbasin

LOCATION.--Lat 35°24'22", long 78°48'48" referenced to North American Datum of 1983, Harnett County, NC, Hydrologic Unit 03030004, on right bank 60 ft downstream of bridge on U.S. Highway 401, 1,860 ft downstream of Southern Railway bridge, 0.5 mi north of Lillington, 1 mi downstream of Neal Creek, and at river mile 178.

DRAINAGE AREA.--3,464 mi².

SURFACE-WATER RECORDS

PERIOD OF RECORD.--December 1923 to current year.

REVISED RECORDS.--WSP 1002: 1930, maximum discharge. WSP 1032: 1942, minimum discharge. WSP 1303: 1944, maximum discharge. WSP 1333: 1945, maximum discharge. WSP 1383: 1924-29, maximum and minimum discharges; 1924-29, daily discharges; 1936, daily discharges. WSP 1703: 1929, daily discharges. WDR NC-81-1: Drainage area.

GAGE.--Water-stage recorder. Datum of gage is 104.62 ft above NGVD of 1929. December 6, 1923 to October 7, 1927, nonrecording gage and October 8, 1927 to December 2, 1975, water-stage recorder at site 60 ft upstream at bridge pier at same datum. Satellite telemetry at station.

REMARKS.--No estimated daily discharge. Records good. Some regulation at high flows, December 1972 to August 1981, caused by temporary storage in B. Everett Jordan Lake. Flow regulated since September 1981 by B. Everett Jordan Lake (station 02098197). Diurnal fluctuation and slight regulation at low flow caused by power plants upstream from station. Fluctuation and regulation by Buckhorn Reservoir, 13 mi upstream from station, ended in December 1962. Prior to regulation, maximum discharge: 150,000 ft³/s, September 19, 1945, from rating curve extended above 76,000 ft³/s; gage height: 33.19 ft, from floodmark; minimum discharge: 11 ft³/s, October 14, 15, 1954; gage height: -0.17 ft. Minimum discharge for period of record also occurred on August 7, 2002. Minimum discharge for current water year also occurred February 22.

Suggested citation: U.S. Geological Survey, 2012, Water-resources data for the United States, Water Year 2011: U.S. Geological Survey Water-Data Report WDR-US-2011, site 02102500, accessed at http://wdr.water.usgs.gov/wy2011/pdfs/02102500.2011.pdf

02102500 CAPE FEAR RIVER AT LILLINGTON, NC—Continued

DISCHARGE, CUBIC FEET PER SECOND
WATER YEAR OCTOBER 2010 TO SEPTEMBER 2011
DAILY MEAN VALUES

Day	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
1	12,200	1,100	606	626	637	831	6,760	850	667	595	592	495
2	10,700	1,390	571	668	661	1,100	5,280	756	975	579	553	470
3	4,920	1,390	555	696	644	1,590	4,220	714	946	574	557	413
4	3,470	1,360	582	704	658	1,940	4,170	667	730	588	580	427
5	2,880	871	751	718	1,280	2,500	2,170	800	672	582	584	456
6	2,610	735	679	715	3,530	2,760	4,240	1,180	657	624	652	471
7	2,380	738	653	701	3,590	2,480	4,320	2,130	635	1,170	666	1,130
8	1,400	709	600	668	3,530	2,820	2,670	1,880	625	991	678	613
9	816	647	577	632	3,650	2,700	1,750	1,740	618	700	597	446
10	687	654	595	607	3,680	1,870	1,660	1,590	588	510	582	436
11	638	574	606	634	3,460	3,430	2,330	1,070	600	912	584	405
12	633	554	630	622	2,260	6,350	5,110	942	587	1,410	566	391
13	546	587	641	623	2,100	5,400	4,670	950	598	1,120	603	418
14	594	570	523	613	1,980	4,600	4,390	1,070	583	938	746	382
15	595	539	492	606	1,040	4,260	4,150	1,560	601	755	1,180	362
16	563	590	559	580	466	3,320	2,360	1,500	592	710	638	427
17	593	665	652	593	412	1,890	2,850	884	587	633	572	436
18	592	655	678	625	376	2,200	4,330	901	574	562	527	413
19	599	656	704	600	393	1,960	4,820	867	589	572	546	396
20	619	643	702	602	355	1,740	4,320	801	581	563	558	389
21	621	629	645	599	315	1,520	2,110	837	565	546	562	391
22	605	649	640	599	577	1,040	1,810	832	624	514	600	601
23	615	617	604	612	659	964	1,470	632	579	491	546	779
24	545	607	601	582	617	981	1,440	565	564	487	531	759
25	547	565	587	557	606	928	1,390	558	603	611	524	1,020
26	565	547	601	626	610	892	1,390	608	673	699	500	1,590
27	572	528	587	621	591	1,170	1,320	684	620	566	542	1,580
28	584	540	609	584	585	2,510	1,560	2,370	647	553	493	1,280
29	522	554	634	607	---	3,560	1,230	1,920	793	633	499	1,530
30	974	561	595	609	---	3,550	964	971	640	636	562	1,880
31	1,140	---	607	624	---	3,600	---	704	---	585	501	---
Total	55,325	21,424	19,066	19,453	39,262	76,456	91,254	33,533	19,313	21,409	18,421	20,786
Mean	1,785	714	615	628	1,402	2,466	3,042	1,082	644	691	594	693
Max	12,200	1,390	751	718	3,680	6,350	6,760	2,370	975	1,410	1,180	1,880
Min	522	528	492	557	315	831	964	558	564	487	493	362
Cfsm	0.52	0.21	0.18	0.18	0.40	0.71	0.88	0.31	0.19	0.20	0.17	0.20
In.	0.59	0.23	0.20	0.21	0.42	0.82	0.98	0.36	0.21	0.23	0.20	0.22

STATISTICS OF MONTHLY MEAN DATA FOR WATER YEARS 1982 - 2011[a], BY WATER YEAR (WY)

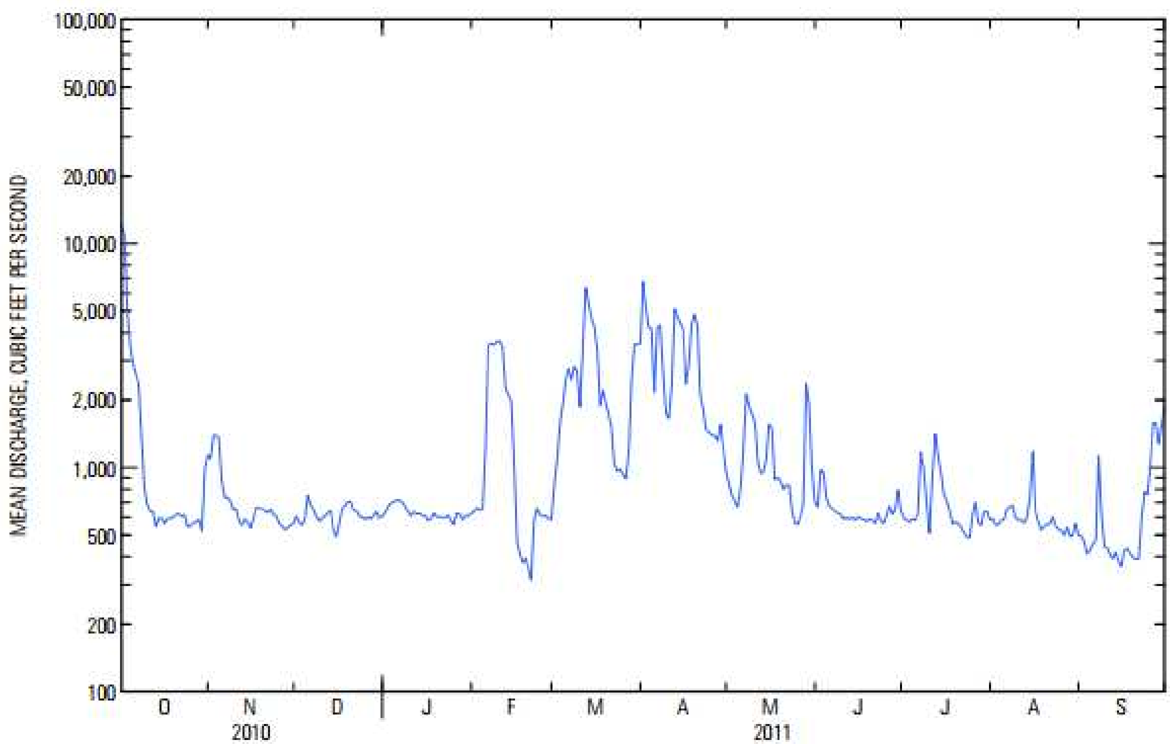
	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Mean	1,772	2,086	2,982	4,537	5,491	6,617	4,720	2,295	2,133	1,567	1,577	1,943
Max	6,442	7,919	8,595	11,750	16,440	15,710	14,780	7,784	12,510	5,694	7,075	13,920
(WY)	(1990)	(1986)	(1984)	(1998)	(1998)	(1993)	(2003)	(1989)	(1982)	(1995)	(2003)	(1996)
Min	317	295	528	628	1,011	1,083	969	642	551	360	274	366
(WY)	(2010)	(2008)	(2008)	(2011)	(2008)	(2006)	(1985)	(2002)	(1999)	(2002)	(2002)	(2007)

02102500 CAPE FEAR RIVER AT LILLINGTON, NC—Continued

SUMMARY STATISTICS

	Calendar Year 2010		Water Year 2011		Water Years 1982 - 2011[a]	
Annual total	948,830		435,702			
Annual mean	2,600		1,194		3,130	
Highest annual mean					7,146	2003
Lowest annual mean					1,013	2002
Highest daily mean	29,700	Feb 6	12,200	Oct 1	41,400	Sep 6, 1996
Lowest daily mean	492	Dec 15	315	Feb 21	155	Aug 6, 2002
Annual seven-day minimum	526	Sep 20	401	Sep 14	206	Oct 9, 2007
Maximum peak flow			7,880	Apr 1	51,800	Sep 7, 1996
Maximum peak stage			6.44	Apr 1	18.97	Sep 7, 1996
Instantaneous low flow			[b]258	Feb 21	[b]141	Aug 6, 2002
Annual runoff (cfsm)	0.750		0.345		0.904	
Annual runoff (inches)	10.19		4.68		12.28	
10 percent exceeds	7,150		2,720		8,910	
50 percent exceeds	751		638		1,170	
90 percent exceeds	562		524		570	

[a] Regulated period only (1981-2011). See Remarks.
[b] See Remarks.



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USGS 02102178 CAPE FEAR R AT BUCKHORN DAM NR CORINTH, NC

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Chatham County, North Carolina
Hydrologic Unit Code 03030004
Latitude 35°32'27", Longitude 78°59'21" NAD27
Drainage area 3,230 square miles
Gage datum 156.49 feet above NAVD88

Output formats
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00065, Gage height, feet,												
YEAR	Monthly mean in ft (Calculation Period: 2008-12-01 -> 2010-05-31)											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2008												1.693
2009			2.355	1.688	1.211	1.586	1.081	1.007	0.966	0.895	1.747	2.455
2010	1.999	2.769	1.71	1.442	1.423							
Mean of monthly Gage height	2	2.77	2.03	1.57	1.32	1.59	1.08	1.01	0.97	0.9	1.75	2.07

** No Incomplete data have been used for statistical calculation

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REGULATORY MINIMUM FLOW REQUIREMENTS

NCDENR
North Carolina Department of Environment and Natural Resources
Division of Water Resources

Michael F. Easley, Governor

William G. Ross Jr., Secretary
John N. Morris, Director

State of North Carolina
B. Everett Jordan Lake Drought Management Plan
(DRAFT)

December 9, 2002

The US Army Corps of Engineers has a Drought Contingency Plan for Jordan Lake.[1] The Corps' Drought Contingency Plan provides an outline of water management measures and coordination actions to consider when a severe drought occurs, but leaves the details of any particular management measures and the timing of their application to be determined as such a drought progresses. The purpose of the State of North Carolina's Jordan Lake Drought Management Plan is to provide more detailed management guidelines consistent with the Corps' Drought Contingency Plan.

I. Relationship with Corps' Drought Contingency Plan

The State's Jordan Lake Drought Management Plan does not supersede the US Army Corps of Engineers' Jordan Lake Drought Contingency Plan. Rather, the State's plan nests within the Corps' plan and provides greater specificity and certainty. The Corps' plan relies on lake elevation as the primary indicator (see figure 1 on the following page). The primary elements of the Corps' plan may be described as follows.[2]

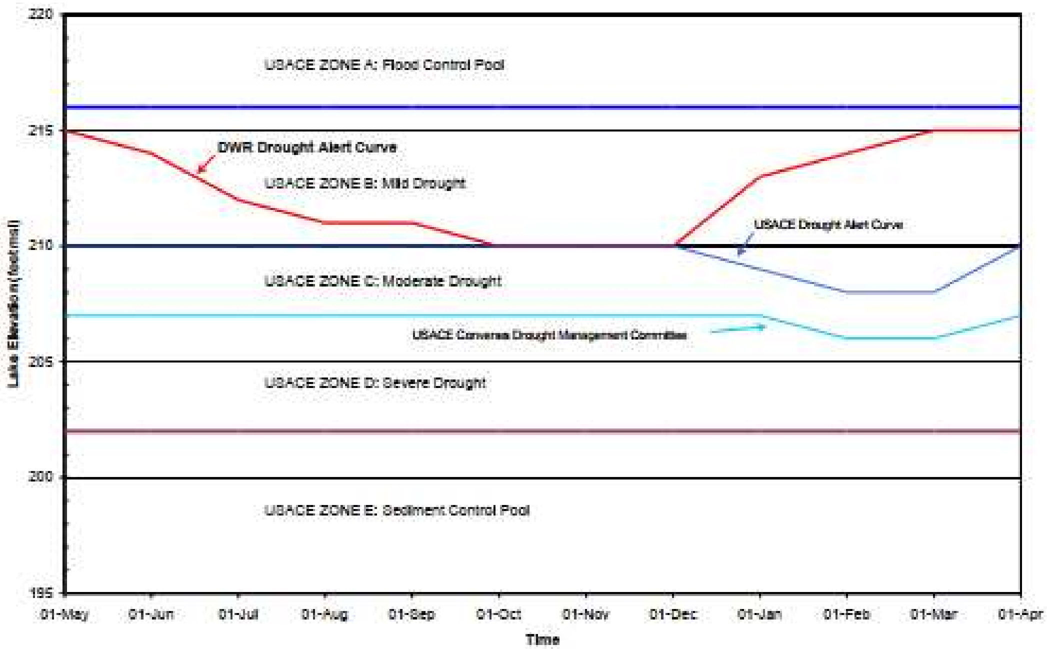
1. When the lake level drops into Zone B (below 216.0 feet msl), the Corps will initiate a water budget. The Corps will update the Division of Water Resources weekly regarding the remaining water supply and water quality storage.
2. When the lake level drops into Zone C, or the water quality storage volume falls below 45 percent as indicted by the water budget, the Corps will initiate coordination between all concerned parties.
3. When the storage volume of either the water supply pool or the water quality pool falls below 23 percent, the Corps will notify DWR that implementation of water conservation should be considered.

[1] B. Everett Jordan Lake Drought Contingency Plan (US Army Corps of Engineers' 1992 Water Control Manual for B. Everett Jordan Project, Exhibit B)
[2] B. Everett Jordan Lake Drought Contingency Plan, pp. B-5 – B-7

1611 Mail Service Center, Raleigh, North Carolina 27699-1611
Phone: 919-733-4064 \ FAX: 919-733-3558 \ Internet: www.ncwater.org

4. When the lake level drops into Zone D, the Corps will convene a Drought Management Committee to discuss a course of action for the continued operation of Jordan Lake and possible alternatives. The Corps' plan then provides a brief list of alternatives.

Figure A1 **Drought Operation Curves**[3]



The Division of Water Resources will obtain daily lake levels for Jordan Lake by automatically downloading the real-time data from the US Geological Survey's web site for station number 02098197. When the lake level drops to the DWR Drought Alert Curve (see figure 1), DWR will work with the Corps to determine if the Haw River Basin is entering a severe drought.

II. Determining a Severe Drought

We will implement drought measures when the Corps and the Division of Water Resources determine that the Haw River Basin is in a severe drought. We will determine a severe drought in the Haw River Basin based on three factors: inflows to Jordan Lake, Jordan Lake level and the time at which these occur during the climatic year. Current Jordan Lake inflows and level will be based on a moving 7-day average. We will rely upon the Corps' calculated inflows to Jordan Lake.

[3] Based on B. Everett Jordan Lake Drought Contingency Plan, Exhibit 1

Table A1 **Drought Response Triggers**

Time (climatic year)	**Jordan Lake Average Daily Level (7-day)** (feet msl)	**Jordan Lake Average Daily Inflow (7-day)** (cfs)	**Drought Response** (target reduction schedule)
April	215	160	Spring-Summer
May	215	70	Spring-Summer
June	214	30	Spring-Summer
July	212	30	Spring-Summer
August	211	30	Spring-Summer
September	211	30	Spring-Summer
October	210	3	Fall-Winter
November	210	20	Fall-Winter
December	210	120	Fall-Winter
January	213	170	Fall-Winter
February	214	270	Fall-Winter
March	215	320	Fall-Winter

When Jordan Lake levels are equal to or less than the value indicated for the given month (i.e., the Drought Alert Curve), the Division of Water Resources will work with the Corps to evaluate Jordan Lake inflows. We will determine a drought is severe in the Haw River Basin and implement the previously described responses whenever Jordan Lake inflows and the Jordan Lake level are both less than the value indicated in Table 1. These drought response triggers coexist with those found in the Corps' plan.

III. Drought Responses

When the Corps and the Division of Water Resources determine that the Haw River Basin is in a severe drought, we will implement the following measures.

Dam Releases

The normal low-flow target at Lillington is 600 cfs, ± 50 cfs.[4] During severe droughts, we will implement a stepped reduction in the target. The stepped flow reduction allows fish time to migrate to deeper water. The stepped flow reduction also provides us time to observe any adverse impacts in water quality.

When we determine that the Haw River Basin is in a severe drought, we will immediately reduce the low-flow target at Lillington to 500 cfs. We will also notify the Division of Water Quality and the Wildlife Resources Commission. The DWQ and the WRC will begin monitoring Cape Fear River water quality and habitat, weekly. Following the first week of monitoring and prior to the next low-flow target reduction, we will meet with the DWQ and the WRC to review available data and adjust the target reduction schedule accordingly. The table on the following page describes the low-flow target reduction schedule for the spring and summer period.

[4] Unless otherwise noted, all flow values are based on a daily average.

Table A2 **Low-Flow Target Reduction Schedule, Spring and Summer**

Time	Lillington Gage		Lock & Dam #1 Gage
	Flow Target (cfs)	Precision (cfs)	Flow (cfs)
Day 1	500	± 50	
Day 8	450	± 50	
Day 15	400	± 50	
Day 22	350	± 50	
Day 29	300	± 25	
Day 36	250	± 25	
Day 42	250	± 25	< 200
	200	± 25	= 200

The low-flow target at Lillington of 200 cfs is based on two considerations. The design of the Jordan Lake Dam service gate is such that the minimum flow that the Corps can release is between 130 cfs and 200 cfs, depending on the current lake level. Harnett County estimates that their water supply intake could not operate at flows less than 190 cfs, measured at the Lillington gage.[5] On day 42 of the target reduction schedule, the flow at Lock & Dam #1 becomes a target. When the flow at Lock & Dam #1 is greater than, or equal to 200 cfs, the flow target at Lillington is 200 cfs. When the flow at Lock & Dam #1 is less than 200 cfs, the flow target at Lillington is 250 cfs.

On Day 29, when the low-flow target at Lillington is reduced to 300 cfs, all water supply systems withdrawing water from the Cape Fear River will implement any necessary measures to reduce the quantity of water they withdraw by 20 percent. The policies associated with this mandatory water withdrawal reduction are provided in a separate document.

During the fall and winter period, the reduction schedule is not as extreme. The following table describes the low-flow target reduction schedule for the fall and winter period.

Table A3 **Low-Flow Target Reduction Schedule, Fall and Winter**

Time	Lillington Gage	
	Flow Target (cfs)	Precision (cfs)
Day 1	500	± 50
Day 8	450	± 50
Day 15	400	± 50
Day 22	350	± 50
Day 29	300	± 25

On Day 29, when the low-flow target at Lillington is reduced to 300 cfs, all water supply systems withdrawing water from the Cape Fear River will implement any necessary measures to reduce the quantity of water they withdraw by 20 percent. The policies associated with this mandatory water withdrawal reduction are provided in a separate document.

[5] Note that the daily average flow at Lillington dropped to 155 cfs on August 6, 2002 and Harnett County's intake continued to operate.

In-Lake Water Supply Withdrawals

Only water supply systems for which the Environmental Management Commission has approved a water supply storage allocation may withdraw water from Jordan Lake. Allocation holders are required to implement Drought and Water Shortage Response Plans during severe droughts, as specified in Articles 3 and 9 of the contracts for Jordan Lake water supply storage allocations.

Jordan Lake Pool Re-Allocation

If the low-flow augmentation pool becomes depleted, other Jordan Lake pools may be temporarily re-allocated to the low-flow augmentation pool. Temporary re-allocations will increase the amount of storage available to support releases of water from Jordan Dam. However, if the lake falls to a level that would jeopardize the ability of allocation holders to withdraw water from their water supply storage, releases for downstream flow augmentation may be restricted, despite the amount of water available from the re-allocated pools. Temporary pool re-allocations will occur under the following triage approach.

Table A4 **Jordan Lake Pool Re-Allocation Triage**

Re-Allocation Priority	**Pool**	**Available Storage** (acre-feet)
	Low-Flow Augmentation Storage	94,600
First	Sediment Storage	74,700
Second	Un-Allocated Water Supply Storage	16,946
Third	Allocated Level II Water Supply Storage	3,664

Temporarily re-allocating the sediment storage to the low-flow augmentation pool requires approval from the Corps. Temporarily re-allocating any of the Level II water supply storage allocations requires the approval of the respective allocation holders. Such a temporary re-allocation would also require the State to reimburse the allocation holders for the limited use.

When the first pool re-allocation occurs, all water supply systems in the Cape Fear River Basin will be required to implement mandatory water use reduction measures designed to achieve at least a 20 percent reduction in water use.

IV. Refilling Jordan Lake

During an extended drought or at the conclusion of a severe drought, refilling Jordan Lake becomes a priority. In general, we will continue to restrict releases from the dam until the lake level is at normal pool. The refill strategy for the lake is described in the table on the following page.

Table A5 **Jordan Lake Refill Strategy**

Jordan Lake Average Level (7-day) (feet msl)	Jordan Lake Average Daily Inflow (7-day) (cfs)	Jordan Lake Release
< 216.0	NA	Low-Flow Target Reduction Schedule
216.0	= 600	Equals Inflow
216.0	> 600	Resume Normal Low-Flow Target

V. Hydrologic Modeling and Analyses

We conducted the following analyses to determine optimal drought triggers, to determine the impacts of the drought plan on lake levels and stream flows, and to verify the effectiveness of the plan.

Drought Response Triggers

We analyzed the historic records of Jordan Lake inflows and Jordan Lake levels to determine the appropriate values for the Drought Response Triggers table. We relied upon data from the Corps for the period of October 4, 1982 to October 20, 2002.

Figure A2 **Jordan Lake Daily Inflows, Period of Record**

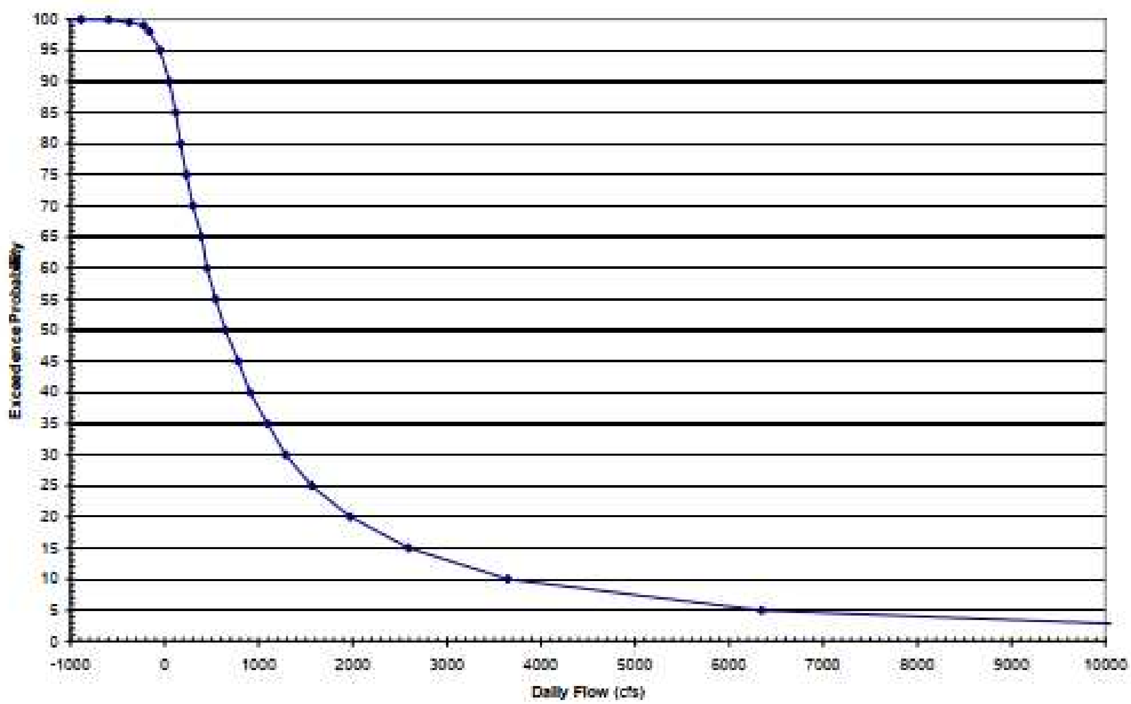


Figure A3 **Jordan Lake Daily Inflows, by Month**

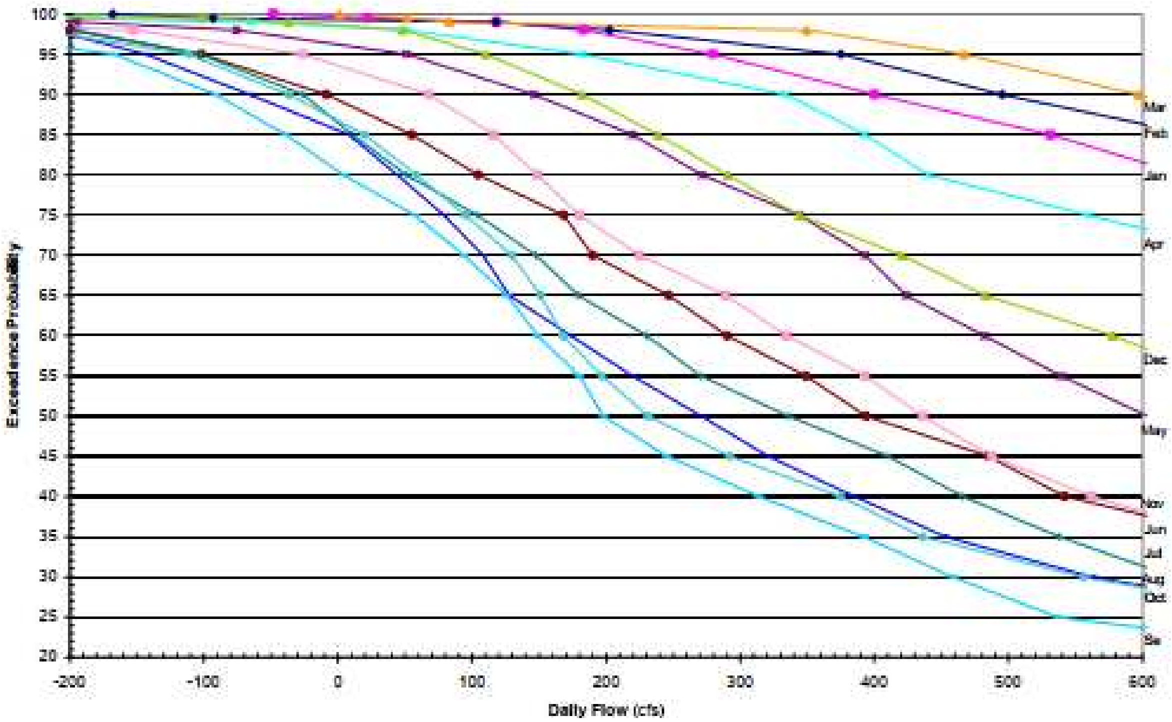


Figure A4 **Jordan Lake Daily Inflows, Statistics by Month and Drought Response Trigger**

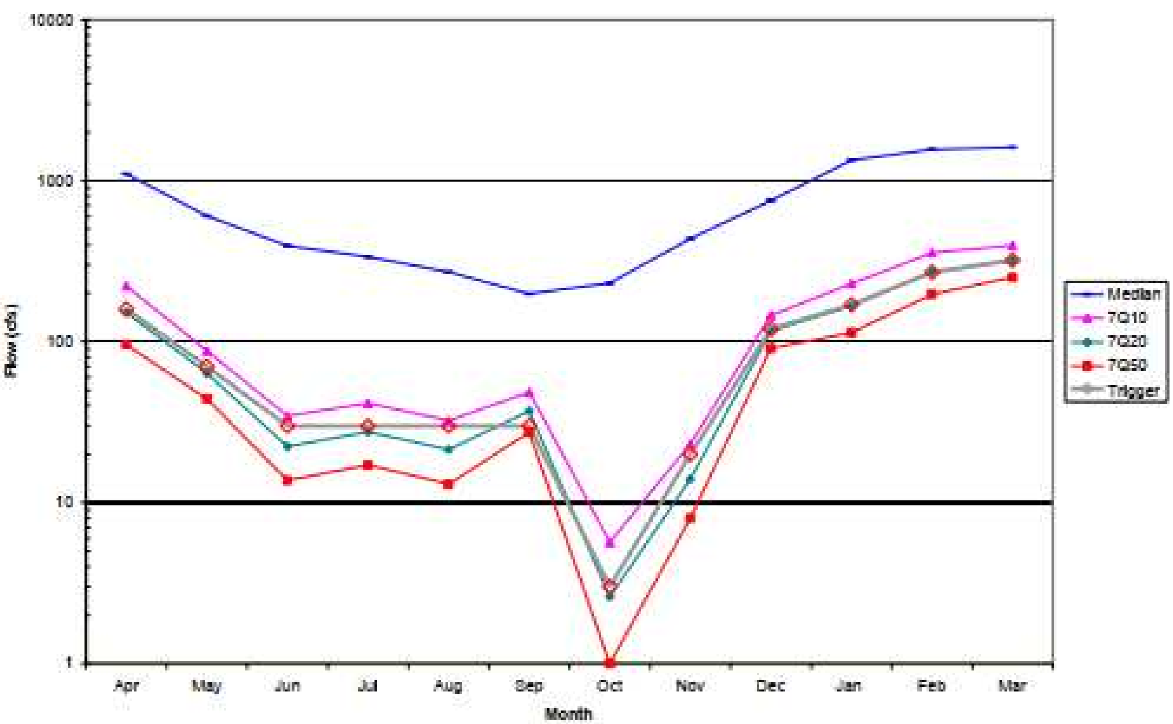


Figure A5 **Jordan Lake Daily Levels, Period of Record**

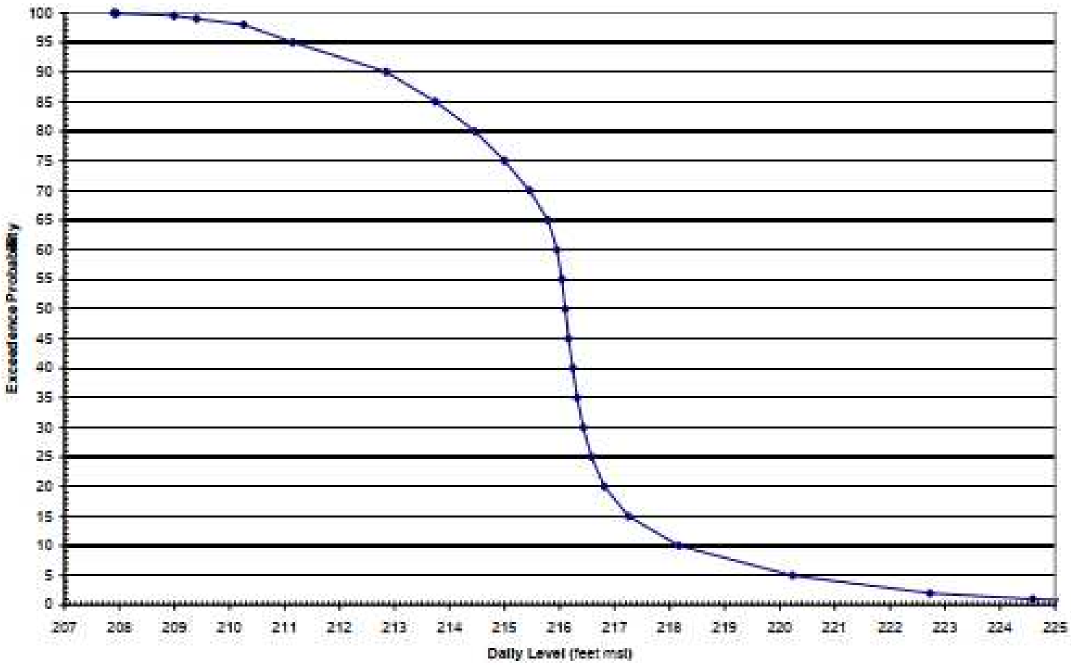


Figure A6 **Jordan Lake Daily Levels, by Month**

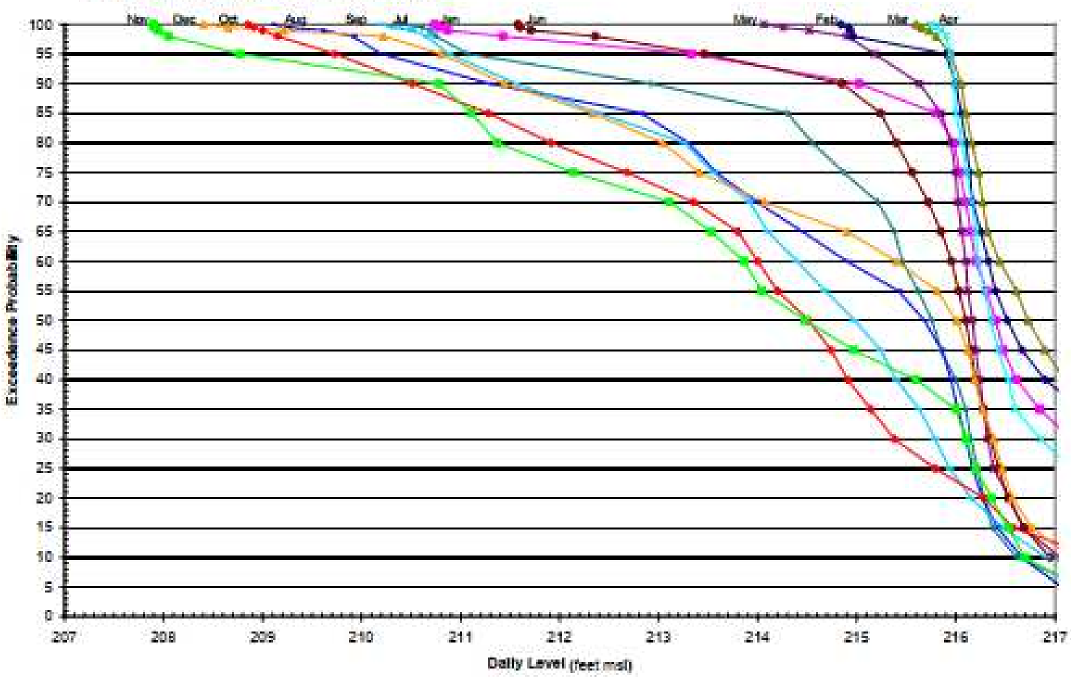
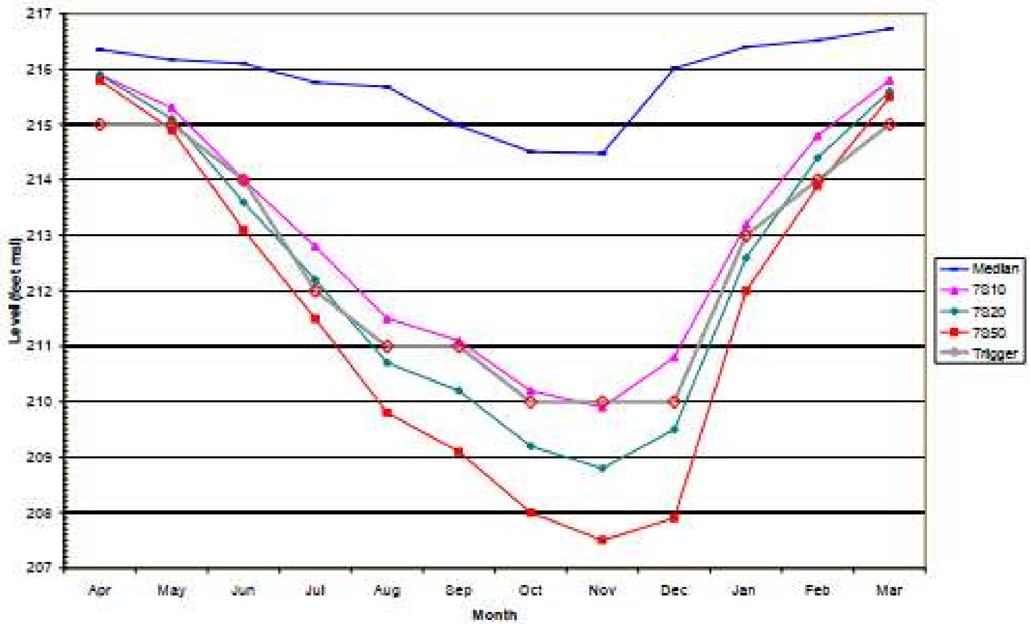


Figure A7 , **Jordan Lake Daily Levels, Statistics by Month and Drought Response Trigger**



Analyzing data for the period from February 4, 1982 to October 31, 2002 provides an indication of the impact the drought management plan will have on lake operations. Had this drought management plan been in effect since the lake was first filled, a drought response would have been triggered six times. The following table describes those events.

Table A6 **Hypothetical Drought Response Events**

Event	Triggered (date)	Jordan Lake Average Daily Level (7-day) (feet msl)	Jordan Lake Average Daily Inflow (7-day) (cfs)	Duration (days)	Normal Operation Resumed (date)	Jordan Lake Average Daily Level (7-day) (feet msl)	Jordan Lake Average Daily Inflow (7-day) (cfs)
1	9/23/1983	210.9	10	73	12/5/1983	216.0	2415
2	6/20/1986	214.0	10	201	1/7/1987	216.0	2037
3	8/23/1988	211.0	-11	104	12/5/1988	216.0	1211
4	9/28/1990	211.0	4	26	10/24/1990	216.0	7220
5	1/1/2002	211.0	122	26	1/27/2002	216.0	4960
6	5/25/2002	214.8	25	141	10/13/2002	216.0	9380

The following six figures provide comparisons of the historic Jordan Lake outflows and the hypothetical, drought response outflows during those six events. Note that the hypothetical drought responses under the drought management plan are similar to the historic drought responses, but the drought management plan generally triggers an earlier and more extreme drought response.

Figure A8 **Hypothetical Drought Response, Event 1**

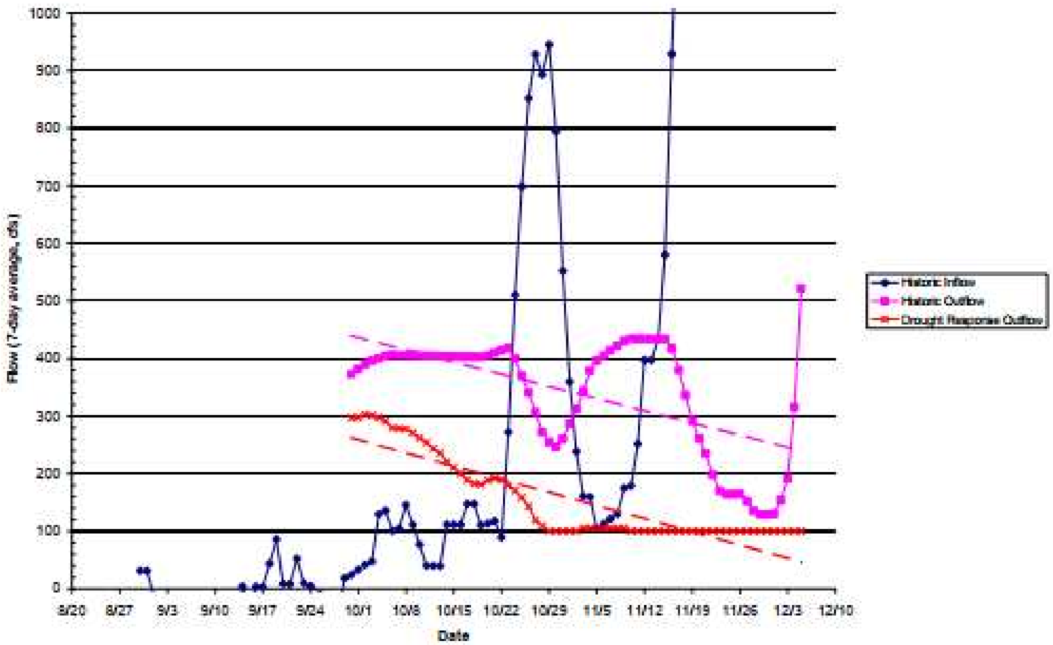


Figure A9 **Hypothetical Drought Response, Event 2**

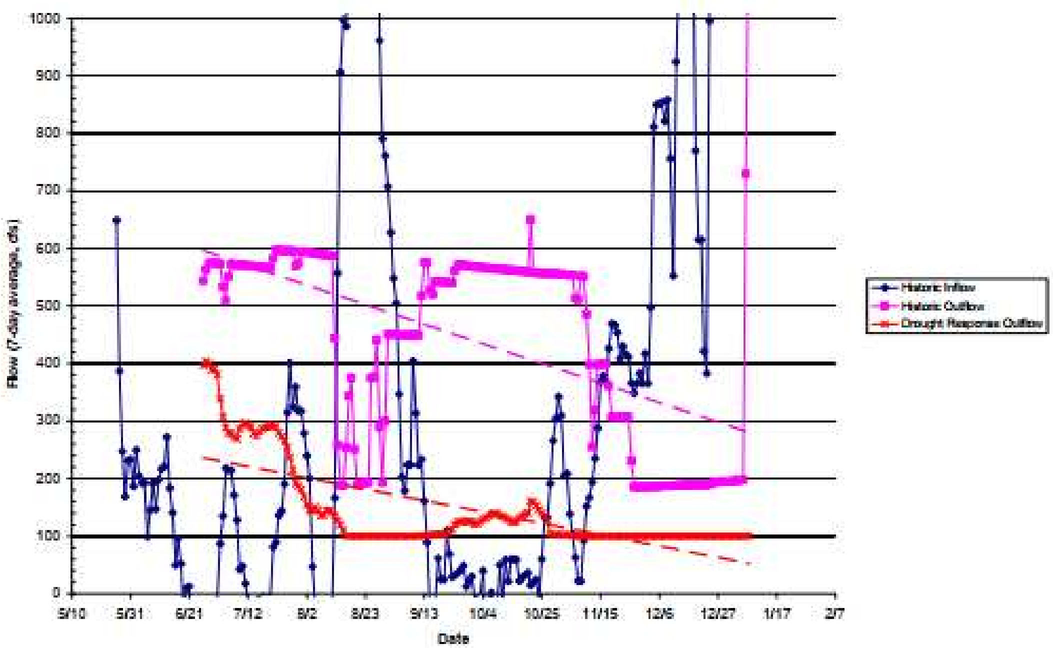


Figure A10 **Hypothetical Drought Response, Event 3**

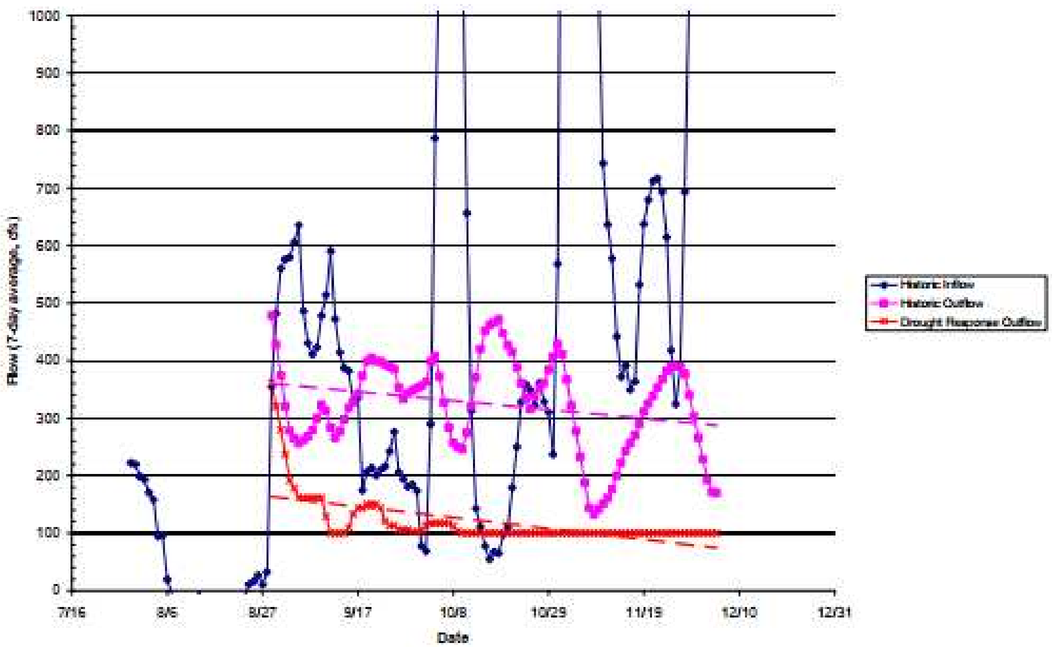


Figure A11 **Hypothetical Drought Response, Event 4**

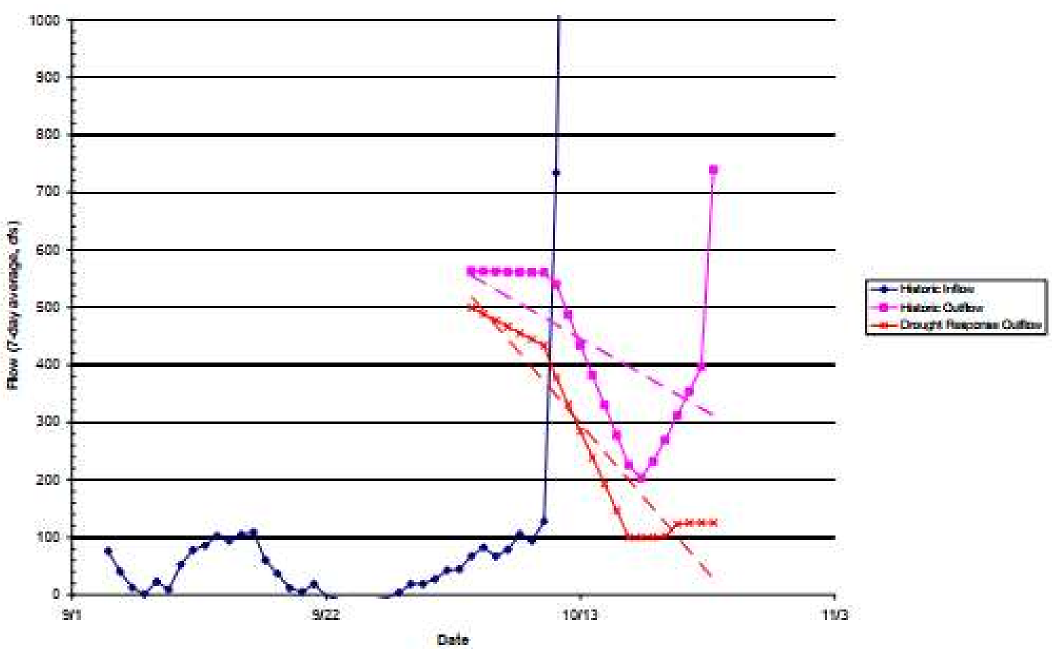


Figure A12 **Hypothetical Drought Response, Event 5**

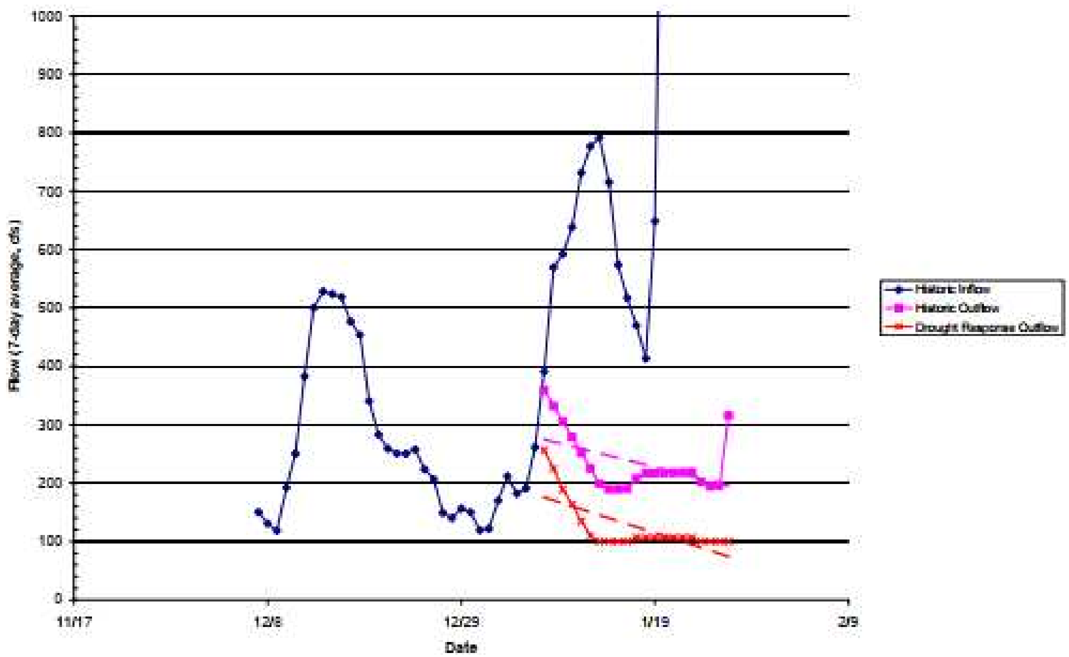
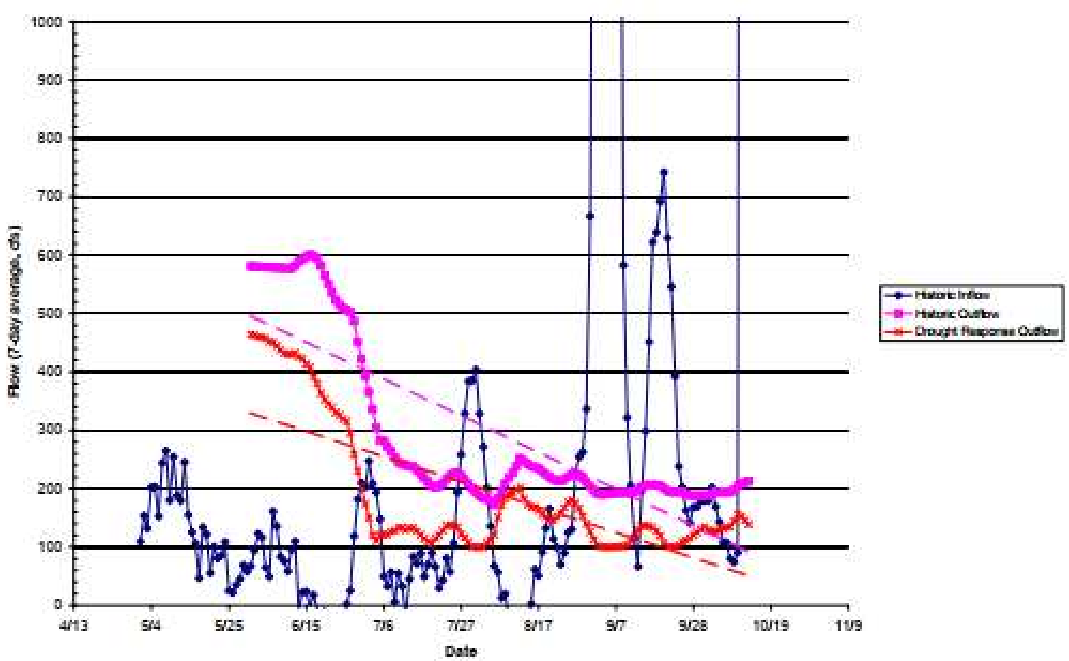


Figure A13 **Hypothetical Drought Response, Event 6**



In-Lake Drought Management Impacts

We must analyze the impacts of the drought management plan on lake levels and outflows, and compare the result with the results obtained from the Cape Fear River Basin Hydrologic Model scenarios (i.e., 1998 Scenario, 2030 Scenario and 2050 Scenario). Lake level analyses are important to understand the potential impacts to water supply withdrawals, recreation and habitat.

We will probably have to use a different model from the Cape Fear River Basin Hydrologic Model to analyze the impacts of the Jordan Lake Drought Management Plan, as the stepped target reduction scheme is not compatible with that model. Jordan Lake inflow results from the CFRBHM scenarios, as well as Deep River outflow results and the relative contributions of the local flows between Jordan Dam and Lillington, will serve as inputs to the Jordan Lake drought management model.

Cape Fear River Drought Management Impacts

We must analyze the impacts of the drought management plan on Cape Fear River flows and compare the result with the results obtained from the Cape Fear River Basin Hydrologic Model scenarios (i.e., 1998 Scenario, 2030 Scenario and 2050 Scenario). We can probably use the Cape Fear River Basin Hydrologic Model for this analysis, as we can use the Jordan Lake release results from the Jordan Lake drought management model as inputs to the Cape Fear model.

SHEARON HARRIS NUCLEAR POWER PLANT DATA

SHEARON HARRIS NUCLEAR POWER PLANT FACT SHEET

Harris Nuclear Plant Fact Sheet

Harris Quick Facts

Groundbreaking: 1978
Commercial operation:
Unit 1 – 1987
Number of units: 1
Reactor type: Pressurized water reactor (PWR)
Station capacity: 964 megawatts, enough to power more than 650,000 homes

General Information

Harris Nuclear Plant is located in New Hill, N.C. on Harris Lake, approximately 22 miles southwest of Raleigh.

Harris plant personnel remain committed to operating the unit safely, reliability and maintaining a good relationship with the community.

- Issued a 20-year extension on its license by the NRC (all U.S. reactors were initially licensed for 40 years).
- The plant is named after Shearon Harris, former president, CEO and chairman of Carolina Power & Light.
- Harris Lake, which supplies cooling water for the plant, includes two boat ramp facilities and a county park that make the lake accessible for fishing, boating and water skiing.

Nuclear Safety

- Nuclear stations have multiple, robust safety barriers in place.
- The containment building housing the nuclear fuel core is 4.5 feet of reinforced concrete with a 3/8 inch-thick steel liner.
- The reactor vessel containing the nuclear fuel is 42.5 feet tall and 13 feet in diameter and constructed of 6-inch-thick steel.
- Harris has redundant safety systems, including multiple pumps and backup electrical supply systems.
- Nuclear stations are built to withstand a variety of external forces, including hurricanes, tornadoes, fires, floods and earthquakes.
- Duke Energy works closely with the Nuclear Regulatory Commission (NRC), various federal agencies, state agencies and local governments to maintain emergency response plans that ensure close coordination with these groups.

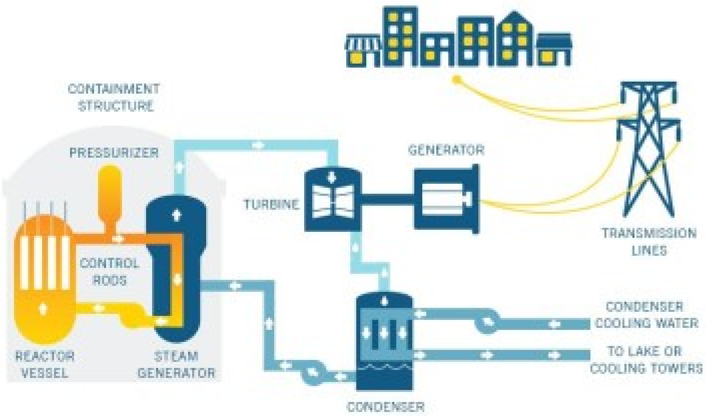
Nuclear Security

- Nuclear stations have numerous security features, seen and unseen.
- Armed, highly-trained security professionals provide 24-hour protection.
- Physical barriers and electronic surveillance systems surround Harris.
- Access is tightly controlled and nuclear employees must pass strict background, psychological and drug/alcohol screenings.

Radiation

- Radiation is a natural part of our environment.
- We receive radiation from the sun, minerals in the earth, food, etc.
- The amount of annual radiation at a nuclear plant site boundary is less than a passenger receives during a round-trip, coast-to-coast flight.

February 2020



Nuclear Fundamentals

Harris Nuclear Plant uses uranium as its fuel. Each uranium pellet, less than one inch long, is enclosed in metal rods 13 feet tall. There are approximately 350 pellets per rod, 264 fuel rods in a fuel assembly and 157 fuel bundles in the reactor core.

In a process called nuclear fission, a source emitting free neutrons is inserted into the uranium fuel core. The uranium fuel absorbs these free neutrons, becomes less stable and releases additional free neutrons. This movement of free neutrons creates heat used to generate electricity.

Here is how it works:

- Water circulates through the nuclear core, reaching 590 degrees F by removing heat from the fission process.
- Neutron absorbing control rods are lowered into the fuel core to slow or stop this process.
- This heated water travels to large steam generators or "heat exchangers."
- This 590-degree F water flows through thousands of tubes inside the steam generators while cooler water circulates on the outside of these tubes and becomes steam.
- The steam flows to a turbine and spins large blades attached to a shaft and generator, producing electricity.
- This steam then flows across a set of tubes containing cool water that condenses the steam for reuse in the steam generators.
- This heated water is returned to a cooling tower where it cools and returns to the plant's condenser system.

Conserving Resources

Because nuclear power plants do not burn fuel, they produce no greenhouse gas emissions while generating electricity. In fact, more than half of America's carbon-free electricity comes from nuclear energy.

Energy & Environmental Center

The Harris Energy & Environmental Center offers an interactive educational experience on electricity generation and transmission, renewable energy, energy efficiency and the benefits of nuclear power. All activities are free.

For more information about the Harris Energy & Environmental Center, visit www.duke-energy.com/eecenter or call 984-229-6261. Individual and group visits are arranged by appointment only Tuesday through Friday, 9 a.m. to 3 p.m.

SHEARON HARRIS NUCLEAR POWER PLANT HISTORICAL ENERGY GENERATION

Generation (MWh) of Shearon Harris Nuclear Power Plant

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual (Total)
2001	651,550	587,897	650,961	600,053	641,046	612,514	633,035	632,278	392,127	-7,612	-7,423	-17,930	**5,368,496**
2002	596,616	605,885	692,186	664,354	685,426	656,254	587,765	633,905	657,210	687,635	670,898	696,922	**7,835,056**
2003	697,798	628,360	692,040	550,040	200,220	585,862	675,487	566,282	586,953	690,227	668,416	695,419	**7,237,104**
2004	696,104	651,056	691,524	640,461	378,332	655,523	674,118	676,491	658,386	324,248	268,635	693,550	**7,008,428**
2005	691,938	627,883	693,146	663,595	577,180	654,438	670,675	671,369	652,216	669,072	664,739	694,577	**7,930,828**
2006	691,473	624,282	689,215	144,735	256,719	651,468	665,897	665,520	588,819	689,625	669,468	692,047	**7,029,268**
2007	691,771	626,054	685,273	660,878	678,022	648,431	666,547	661,605	600,239	137,065	667,641	679,524	**7,403,050**
2008	692,158	644,233	684,058	661,179	679,592	648,293	672,513	436,426	656,281	686,147	668,900	691,631	**7,821,411**
2009	693,809	624,890	688,165	342,241	441,456	659,020	680,311	678,090	657,569	689,492	551,057	697,061	**7,403,161**
2010	690,254	632,140	695,980	666,054	685,081	654,660	677,181	677,639	653,802	11,904	336,596	699,324	**7,080,615**
2011	695,889	622,800	697,118	668,969	685,747	657,595	676,763	678,847	661,806	693,847	675,050	697,696	**8,112,127**
2012	700,273	654,589	692,354	421,429	-7,575	461,809	691,734	698,837	681,896	711,705	692,239	715,075	**7,114,365**
2013	716,430	638,321	692,542	683,333	324,651	512,112	696,829	645,140	656,853	708,893	175,051	438,208	**6,888,363**
2014	606,998	645,639	714,360	684,365	535,765	670,317	696,617	698,502	678,978	709,000	692,342	715,692	**8,048,575**
2015	716,758	650,304	712,106	15,096	333,847	671,653	695,019	696,555	677,127	706,975	692,525	704,212	**7,272,177**
2016	716,122	673,699	712,660	687,985	706,362	676,975	695,043	696,569	672,401	136,077	416,053	723,105	**7,513,051**
2017	721,046	643,988	717,641	688,333	709,239	680,788	698,805	701,133	674,279	556,960	697,080	719,281	**8,208,573**
2018	593,388	643,338	715,370	128,815	459,520	701,420	724,583	723,583	701,214	733,607	721,164	741,912	**7,587,914**
2019	744,045	669,919	737,793	704,407	720,979	691,860	708,692	710,988	687,739	221,209	268,342	744,621	**7,610,594**
2020	743,483	694,486	677,007	716,207	735,529	621,287	716,872	649,871	702,747	732,024	715,179	570,901	**8,275,593**
2021	741,049	668,251	740,789	529,499	364,993	605,624	721,395	719,843	702,654	732,369	720,298	739,969	**7,986,733**
2022	745,709	670,409	739,405	671,858	725,765	699,163	716,382	647,562	0	0			**5,616,253**
Average per year													**7,568,349**
Average per day													**20,735**

"Electricity Data Browser". www.eia.gov. Retrieved 2023-01-08.

SHEARON HARRIS RESERVOIR HISTORICAL LAKE LEVELS

Kim E. Maza
Vice President
Harris Nuclear Plant
5413 Shearon Harris Road
New Hill, NC 27562-9300

March 15, 2021
Serial: RA-21-0097

ATTN: Document Control Desk
U.S. Nuclear Regulatory Commission
Washington, DC 20555-0001

Shearon Harris Nuclear Power Plant, Unit 1
Docket No. 50-400/Renewed License No. NPF-63

Subject: Notification of Permit Revision Request Regarding Copper and Zinc Limits

Ladies and Gentlemen:

In accordance with Section 3.2 of the Environmental Protection Plan (Nonradiological), issued as Appendix B to the Renewed Facility Operating License No. NPF-63 for the Shearon Harris Nuclear Power Plant, Unit 1, Duke Energy Progress, LLC (Duke Energy), is providing notification of a National Pollutant Discharge Elimination System (NPDES) revision request for removing copper and zinc limits from Outfall 006 within NPDES Permit No. NC0039586. A copy of the NPDES revision request is provided in the enclosure to this letter. The NPDES permit revision request has been submitted to the State of North Carolina permitting agency.

Please refer any questions regarding this submittal to Bob Wilson at (984) 229-2444.

Sincerely,

Kim E. Maza

Kim E. Maza

Enclosure: Permit Revision Request Regarding Copper and Zinc Limits

cc: J. Zeiler, NRC Senior Resident Inspector, HNP
M. Mahoney, NRC Project Manager, HNP
NRC Regional Administrator, Region II

ENCLOSURE

PERMIT REVISION REQUEST REGARDING COPPER AND ZINC LIMITS

DUKE ENERGY.

Kim E. Maza
Vice President
Harris Nuclear Plant
5413 Shearon Harris Rd
New Hill, NC 27562-9300

FEB 24 2021

Serial: RA-21-0080

Certified Mail Number: 7014 2120 0003 3196 7224
Return Receipt Requested

Mr. Danny Smith, Director
NC DEQ Division of Water Resources
512 N. Salisbury Street
Raleigh, NC 27604

Subject: Duke Energy Progress, LLC (Duke Energy) – Shearon Harris Nuclear Power Plant
NPDES Permit No. NC0039586, Wake County
Clarifications to Mixing Zone Modeling & Analysis

Dear Mr. Smith:

The 2016 NPDES Permit for Duke Energy's Shearon Harris Nuclear Power Plant (HNP) included new effluent limits for copper and zinc at Outfall 006, which discharges into Harris Lake. This permit, effective September 1, 2016, required compliance with these new limits by September 30, 2021. In accordance with the strategy outlined in the Corrective Action Plan (CAP), submitted to NC DEQ's Division of Water Resources (DWR) in September 2017, Duke Energy has expanded sampling and effluent characterization, employed water chemistry management strategies, and completed specialized testing and site-specific engineering studies.

In August 2020, as part of these compliance activities, Duke Energy submitted the results of a Mixing Zone Study (Study), completed at the request of DWR. The Study used EPA guidance and national best practices to complete hydrodynamic modeling of mixing zones, evaluate acute and chronic mixing zone boundaries, and calculate dilution effects. In November, Duke Energy and DWR held a video conference call to address DWR questions about the Study.

At this meeting, DWR raised two questions regarding the CORMIX hydrodynamic model and recommended additional modeling runs to validate results. Although originally requesting additional review time, DWR confirmed by email on December 11th, that their review was complete, and they had no additional questions or concerns. After performing the requested additional modeling runs, responses to DWR's two inquiries were detailed in the enclosed Technical Memorandum (TM).

Duke Energy trusts DWR is satisfied with the responses and supplemental modeling provided in the TM. Duke Energy requests the Study be approved, and the conclusions implemented to remove the copper and zinc limits from Outfall 006 within NPDES Permit No. NC0039586. Duke Energy respectfully requests the removal of copper & zinc limits associated with Part I (A)(6) Effluent Limitations and Monitoring Requirements (Outfall 006) and the compliance language and date of September 30, 2021 as addressed in Part I (A)(9) Schedule of Compliance (Outfall 006). A check for $1,030 made payable to NC DEQ DWR for the major permit modification processing fee is enclosed. Duke Energy remains committed to continued compliance at HNP and requests DWR issue an appropriate permit revision as soon as practicable but prior to the current NPDES permit expiration date of August 31, 2021.

I certify, under penalty of law, that this document and all attachments were prepared under my direction or supervision in accordance with a system designed to assure that qualified personnel properly gather and evaluate the information submitted. Based on my inquiry of the person or persons who manage the system, or those persons directly responsible for gathering the information, the information submitted is, to the best of my knowledge and belief, true, accurate, and complete. I am aware that there are significant penalties for submitting false information, including the possibility of fines and imprisonment for knowing violations.

Sincerely,

Kim E. Maza

Kim E. Maza
Vice President, Harris Nuclear Plant
Duke Energy Progress, LLC

Enclosures: **Check for Major Permit Modification Processing Fee**

Technical Memorandum, Clarifications to Mixing Zone Modeling & Analysis, February 12, 2021

cc: Mr. Sergei Chernikov, Environmental Engineer III, NPDES Industrial Permitting
Certified Mail Number: 7014 2120 0003 3196 7262
Return Receipt Requested

Mr. Scott Vinson, Water Resources Regional Supervisor
Certified Mail Number: 7014 2120 0003 3196 6517
Return Receipt Requested

Ms. Cyndi Karoly, Chief, Water Sciences Section, NC DEQ DWR
Certified Mail Number: 7014 2120 0003 3196 7286
Return Receipt Requested

Mr. David Hill, Environmental Specialist II, NPDES Industrial Permitting
Certified Mail Number: 7014 2120 0003 3196 7231
Return Receipt Requested

Mr. Nick Coco, Environmental Engineer, NPDES Permitting
Certified Mail Number: 7014 2120 0003 3196 7248
Return Receipt Requested

NCDEQ DWR Central Files
Certified Mail Number: 7014 2120 0003 3196 7255
Return Receipt Requested

NC DEQ Division of Water Resources
Serial: RA-21-0080
Enclosures

Harris Nuclear Plant
NPDES Permit No. NC0039586

Check for Major Permit Modification Processing Fee

Submittal of Technical Memorandum, Clarifications to Mixing Zone Modeling & Analysis

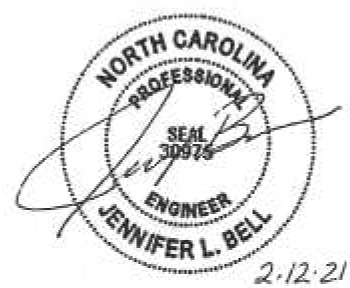
(46 pages including cover)

Jacobs

Technical Memorandum

111 Corning Road, Suite 200
Cary, North Carolina 27518
+1.919.859.5000
+1.919.859.5151 (fax)
www.jacobs.com

Subject	**Shearon Harris Nuclear Plant - Permit NC#0039586 Clarifications to Mixing Zone Modeling & Analysis**
Project Name	Shearon Harris Nuclear Plant NPDES Permit Assistance
Project No.	D33934.02
Date	February 11, 2021
Prepared for	Duke Energy Progress, LLC (Duke Energy)
Prepared by	Jennifer Bell, PE – CH2M HILL North Carolina, Inc. (Jacobs) Brad Paulson – Jacobs



2.12.21

Executive Summary

In July 2019, as a response to Duke Energy's submittal of a Water Effect Ratio Study, the North Carolina Division of Water Resources (DWR) requested that a dye dispersion study or dilution modeling be completed to augment the WER Study results and further inform the development of permit limits for Total Recoverable Copper at Outfall 006 of the Shearon Harris Nuclear Plant (HNP) discharging into Harris Lake. Accordingly, Duke Energy conducted a mixing zone study following U.S. Environmental Protection Agency (EPA) guidance and using the Cornell Mixing Zone Expert System (CORMIX).

The results of that study, submitted in August 2020, indicated significant dilution effects occur at Outfall 006. Within the model, the least favorable of eight seasonal cases predicted a dilution factor of 15.3 (or 6.5% Instream Water Concentration [IWC]) at the acute mixing zone boundary, equivalent to an allowable daily maximum of 166.1 µg/L for Total Recoverable Copper.

After reviewing the Mixing Zone Study, DWR had two questions regarding the CORMIX model:

1. Is the modeling algorithm for a "Heated Discharge" different than what is used for the "Conservative Pollutant" option?
2. What is the sensitivity of the model to variations in Reservoir levels?

Responses to these two inquiries are detailed in this Technical Memorandum (TM) and were confirmed with additional CORMIX model runs. In both cases, the model results reaffirmed the conclusion that, when dilution effects are considered, the maximum predicted copper concentration at Outfall 006 (calculated by DWR Reasonable Potential Analysis spreadsheets) is less than half of the allowable limit.

TABLE 1.
Dilution Factors & Equivalent Copper Effluent Limits from Additional CORMIX Cases

	CORMIX-Calculated Dilution Factor	**Daily Maximum** (Acute)	**Monthly Average** (Chronic)
Results from Original CORMIX Model in Mixing Zone Study	15.3	166.1 µg/L	166.1 µg/L [a]
Results Using "Conservative Pollutant" Option	15.3	166.1 µg/L	166.1 µg/L [a]
Results Using Minimum (*10th percentile*) Reservoir Water Levels	15.0	163.0 µg/L	163.0 µg/L [a]
Maximum Values at Outfall 006 – *Jan 2016 to July 2020*		**63.5 µg/L**	**32.7 µg/L**

[a] The resulting calculated limit for monthly average exceeds the calculated limit for daily maximum (or acute conditions). Therefore, the acute condition governs and the Daily Max and Monthly Average limits are equivalent.

1. Introduction

Duke Energy conducted a mixing zone study evaluating the dilution provided for the discharge from Outfall 006 from Shearon Harris Nuclear Plant (HNP) into Shearon Harris Reservoir under National Pollutant Discharge Elimination System (NPDES) Permit No. NC0039586, effective September 1, 2016.

Prior to initiating modeling, a plan for the Mixing Zone Study was submitted to DWR on November 15, 2019, which included proposing using CORMIX for dilution modeling. Email approval of the study plan was received from DWR with the following recommendations:

- Ambient data collected since 2017 needs to include seasonal measurements of velocity, temperature, and density at the site of discharge and anticipated plume; and
- The thermocline should be sufficiently characterized and modeled as a boundary condition where appropriate.

Both ambient current and seasonal density gradients were addressed and incorporated into the modeling approach. CORMIX modeling results and mixing zone analysis were summarized in the ***Mixing Zone Study*** (Study), dated August 14, 2020, which was submitted concurrently with the ***Year 4 Activities Report*** for the Corrective Action Plan, dated August 19, 2020.

Duke Energy requested the opportunity to discuss both the Study and the conclusions summarized in the Year 4 Activities Report with DWR and to address any questions or concerns. A video conference call was held on November 2, 2020, with Duke Energy, DWR, and Jacobs personnel. Meeting minutes for this video conference are included as Attachment A.

While DWR expressed confidence in the overall approach and information they had reviewed, two specific questions were raised by David Hill regarding the CORMIX model:

1. Is the modeling algorithm for a "Heated Discharge" different than what is used for the "Conservative Pollutant" option, and how are the predicted dilution factors and plume dimensions affected?
2. What is sensitivity of the model results to variations in key input parameters such as reservoir levels?

Responses to these two inquiries are detailed in the following sections and were evaluated with additional CORMIX model runs. A representative sample of the validating runs was selected for each section and output data included as Attachment B and Attachment C, respectively.

2. Temperature Dispersion Versus Conservative Constituent Dilution

In accordance with the approved study plan, the CORMIX hydrodynamic modeling system (CORMIX-1 module) was used to calculate the dilution and associated plume dimensions for a range of effluent and ambient conditions. CORMIX is an EPA-supported empirical modeling system based on experimentally derived curve-fit equations that predict dilution and verify the accuracy of theoretical models. The model emphasizes prediction of the near-field geometry and dilution, although it also predicts the behavior of the discharge plume beyond initial mixing (e.g., in the far-field).

2.1 CORMIX Pollutant Types

The inputs for 'pollutant type' in CORMIX allow for five types of pollutant discharges (described in Section 4.3.1 of the CORMIX User Manual [Doneker and Jirka, 2007]). Specifically, these pollutant types are as follows:

1. **Conservative Pollutant** – no decay or growth processes occur; pollutant of concern can be in any unit of concentration (e.g., µg/L, °C, ppm, or %)
2. **Non-conservative Pollutant** – first-order decay or growth processes occur; pollutant of concern can be in any unit of concentration (e.g., µg/L, °C, ppm, or %)

3. **Heated Discharge** – capable of modeling heat loss to the atmosphere using a specified surface heat exchange coefficient, which is a function of wind velocity and ambient receiving water temperature; discharge dilution/concentration is shown in terms of thermal properties or "heat concentration" (shown as °C)
4. **Brine Discharge** – discharge density greater than ambient density (e.g., desalination by-product); may also include a pollutant concentration of interest (conservative/non-conservative/heated discharge)
5. **Sediment Discharge** – discharge density greater than ambient density with settling particles (e.g., discharge with suspended sediments); may also include a pollutant concentration of interest (conservative/non-conservative)

The two pollutant types directly applicable to effluent at Outfall 006 are 1) 'conservative pollutant' (i.e., effluent properties considered in the Study, such as zinc and copper concentrations or hardness – do not experience decay in freshwater) and 3) 'heated discharge'.

2.2 Selection of a "Pollutant Type" for HNP's Outfall 006

In modeling Outfall 006 (or any freshwater discharge) in CORMIX, thermal data – both effluent and ambient – is essential to predict discharge behavior, as temperature is equivalent to relative density, which governs hydrodynamics. Whether using pollutant TYPE 1 or TYPE 3 in the CORMIX model, the same thermal input is required, and all versions of Outfall 006 have a discharge which is "heated" (warmer than ambient temperatures).

The only meaningful distinction between the "conservative pollutant" and "heated discharge" options is that the latter has the added functionality of modeling atmospheric heat loss, if applicable, using a surface heat exchange coefficient (based on wind velocity and ambient water temperatures). This functionality is more useful when looking at far-field effects (i.e., when the plume behavior is impacted by ambient conditions more than initial discharge velocity) or where a shallow discharge allows for significant plume-surface interaction with a high heat exchange coefficient.

For purposes of the Study, only near-field effects were evaluated, and surface heat losses were not expected to be impactful at Outfall 006, considering its depth and the presence of a thermocline in Summer and Fall. However, unless a non-conservative property is being evaluated, Jacobs typically defaults to the 'Heated Discharge' type when generating new model scenarios. In general, this is a more robust option in the event that surface heat-losses do impact an analysis.

2.3 Concurrence from CORMIX Software Developer

As mentioned above, in the absence of atmospheric heat losses, both the "conservative pollutant" and "heated discharge" options are essentially identical in their predictive algorithms. In theory, if a model is run with a surface heat exchange coefficient of zero (or near zero), or if a predicted discharge plume does not come in contact with the surface, CORMIX results – including centerline dilution and plume geometry – from either pollutant type should be fully identical.

To confirm our understanding of the CORMIX model algorithms and Pollutant Type functionality, Jacobs reached out to the software developer (MixZon, Inc.) on November 9, 2020. Senior Software Engineer Adi S. Ramachandran explained, "assuming all CORMIX model input parameters are the same, CORMIX should predict the same flow class [and thereby provide the same predictions] when specified as using the 'Conservative Pollutant' vs 'Heated Discharge' pollutant options." He further noted that – due to the ability of the "Heated Discharge" option to model atmospheric heat loss – results CAN vary in cases where there is a "loss of buoyancy in a positively buoyant surfacing plume due to ... surface heat exchange, mainly in the buoyant spreading regions of the prediction."

2.4 Validation of Study Model Results Using the "Conservative Pollutant" Type

To further validate the assertion that in the absence of atmospheric heat losses "conservative pollutant" and "heated discharge" produce identical results, CORMIX cases from the Study were rerun using the TYPE 1 "Conservative Pollutant" option using copper concentration as the material of interest, rather than temperature. For the Summer/Fall cases (Cases 3a, 3b, 4a, and 4a), where the thermocline "traps" the plume and prevents any surface interaction, the output data showed 100% identical plume data and dilution factors, as expected. Output for the modified Case 4a, using the "Conservative Pollutant" type, is included in Appendix B as a representative sample of these validating model runs.

For the Winter/Spring cases (Cases 1a, 1b, 2a, and 2a), where the plume is exposed to the surface (and potential atmospheric heat loss), output data was nearly identical. Output used in the Study (all near-field predictions) was the same for both "Conservative Pollutant" and "Heated Discharge" options. The anticipated mathematical variations in output – due to the difference in treatment of surface heat losses – were almost undetectable and statistically meaningless (i.e., within the ability of the model to resolve). For example, in Case 1a, the first difference in predicted dilution is notable at a location 1717 m from Outfall 006, where the pollutant TYPE 1 option predicted dilution of 54.4 and the TYPE 3 option predicted 54.5.

3. Parametric Evaluation of Changing Reservoir Levels

As with any computer model, simplifying assumptions were made to provide input values to CORMIX that simulate effluent properties and ambient conditions at Outfall 006. These model inputs and assumptions are detailed in Section 3 of the Study TM, including their source and/or basis for their selection.

In accordance with DWR's recommendations, seasonal variations for temperature profiles and effluent flow velocities were captured by running separate model cases for each season and utilizing average or maximum values, as appropriate. Model sensitivity to these key input parameters can be seen in the variation of predicted dilution factors at the acute mixing zone boundary, ranging from 15.3 to 27.2.

For most other inputs, however, static values were selected to best reflect "typical" or "most probable" conditions at Outfall 006. Water depth is an example of this kind of static variable. During the video conference call in November 2020, DWR requested a parametric evaluation be performed to illustrate the model's sensitivity to changes in static inputs, recommending reservoir levels be examined.

3.1 Historic Shearon Harris Reservoir Levels

In the Study, water depth parameters (detailed in Section 3.2) were calculated using the Shearon Harris Reservoir normal pool elevation of 220 ft (National Geodetic Vertical Datum [NGVD]). To establish an appropriate range of elevations to use in the requested parametric evaluation, historical data from reservoir level meters in the HNP Primary and Secondary Intake Pumping Station were analyzed.

The table below shows the low (10th percentile), high (90th percentile), and median daily reservoir levels for the six-year period from January 2015 to November 2020. A copy of the complete data set is included as Attachment D.

TABLE 2
Summary of Daily Reservoir Levels from January 2015 to November 2020

	Case 1: Winter *Dec – Feb*	**Case 2: Spring** *Mar – May*	**Case 3: Summer** *Jun – Aug*	**Case 4: Fall** *Sep – Nov*	**Year Round**
Low Water Level *(10th percentile)*	217.5 ft NGVD	219.8 ft NGVD	219.0 ft NGVD	218.0 ft NGVD	**218.8 ft NGVD**
High Water Level *(90th percentile)*	221.0 ft NGVD	220.9 ft NGVD	220.5 ft NGVD	220.7 ft NGVD	**220.8 ft NGVD**
Median Level *(50th percentile)*	220.3 ft NGVD	220.3 ft NGVD	219.8 ft NGVD	219.7 ft NGVD	**220.0 ft NGVD**

As shown here, Shearon Harris Reservoir levels have been historically stable over the past six years, even in periods of extreme drought. While this supports the use of the normal pool elevation (220 ft NGVD) in the original Study, a parametric evaluation which explores sensitivity to a -2 ft /+1ft variability is helpful in validating the model and clarifying predicted behavior.

Case 4a (Fall season, Maximum Day discharge) was selected for the parametric evaluation, as it was the most restrictive model scenario, predicting the least dilution in the acute mixing zone. Additionally, a Fall or Summer case is expected to be more sensitive to changes in water level, as the CORMIX model predicts the discharge plume is trapped by the thermocline, restricting the volume available for dispersion. Of the two seasons with "stratified" conditions, Fall had the greatest pool variability, according to the historic level data.

3.2 Input Parameters Affected by Pool Elevation

In the parametric evaluation, two input values were recalculated to adjust for changes in pool elevation:

- **Height/Depth at Discharge Location (HD)** – height to the water surface measured from the reservoir floor (sediment bottom); calculated as the difference between pool elevation and estimated bottom elevation at Outfall 006 (175 ft NGVD from available bathymetric survey data)
- **Height of Thermocline (HINT)** – height to the thermocline measured from reservoir floor; calculated by deducting the depth to the thermocline (estimated to be 5 m [16 ft] below the water surface) from the total Height at Discharge Location (HD)

The calculated input values used in the revised model runs for the parametric evaluation are shown in bold below.

TABLE 3.
Summary of Revised CORMIX Model Input Parameters

	Normal Pool Level *Median – All Seasons*	Low Water Level *10th Percentile for Fall*	High Water Level *90th Percentile for Fall*
Reservoir Pool Elevation	220 ft NGVD	218 ft NGVD	221 ft NGVD
Estimated Bottom Elevation at Discharge	175 ft NGVD	175 ft NGVD	175 ft NGVD
Height/Depth at Discharge (HD)	45 ft (13.7 m)	**43 ft (13.1 m)**	**46 ft (14.0 m)**
Height of Thermocline (HINT)	29 ft (8.7 m)	**27 ft (8.1 m)**	**30 ft (9.0 m)**

3.3 Parametric Evaluation Results and Conclusions

Case 4a (Fall Season, Max Day Discharge) was modified to reflect alternative scenarios with low and high water conditions. Output for the Low Water Level variation of Case 4a is included in Appendix C. The CORMIX model results are summarized below for the original and alternative scenarios. As described in Section 3.1, the results confirm the plume is impacted by the thermocline, which acts as an upper boundary. Compared to the original Study Case 4a, the low water scenario further restricts the vertical movement of the plume, slightly expanding the width and reducing predicted dilution by less than 2%. Conversely, the high water scenario raises the thermocline, allowing for a slight increase in vertical movement and narrower plume. The impact on dilution was negligible for the high water scenario.

TABLE 4.
CORMIX Case 4a (Original & Variations) Results at EPA-defined Acute Mixing Zone Boundary

CORMIX Case 4a	Radial Distance [a]	Horizontal Distance [a]	Plume Width	Centerline Dilution Factor	IWC	Equivalent Effluent Limit *Acute Copper (Daily Max)*	
Original Study	177 ft	175.5 ft	278.1 ft	15.3	6.54%	166.1 µg/L	-
High Water Level		175.6 ft	277.0 ft	15.3	6.54%	166.1 µg/L	-
Low Water Level		175.9 ft	279.6 ft	15.0	6.67%	163.0 µg/L	-1.9%

Notes:

[a] The radial distance is a vector distance from the center of the port, while the horizontal distance reflects the x-direction only (plan view, looking down at the surface of the waterbody)

For purposes of dilution at an acute mixing zone boundary, the Low Water Level Case 4a represents a "worst-case of the most conservative case" scenario. Notably, the predicted dilution factor at the acute mixing zone boundary of 15.0 is equivalent to an effluent limit of 163.0 µg/L, which is greater than double the maximum value measured at Outfall 006.

4. References

Doneker, R.L., and G.H Jirka. 2007. *CORMIX User Manual. A Hydrodynamic Mixing Zone Model and Decision Support System for Pollutant Discharges into Surface Waters.* EPA-823-K-07-001. December 2007.

Duke Energy. 2020. *Corrective Action Plan for Copper and Zinc for Harris Nuclear Plant NPDES Permit, Year 4 Activities Report.* Submitted to North Carolina Department of Environmental Quality on August 27, 2020.

APPENDIX B: UPDATED RAINFALL FREQUENCY ANALYSIS

2000 RAINFALL ESTIMATES			
Percent Chance	Mean Curve	Adjusted Estimates	
Exceedance	mm/day	mm/day	inches/day
0.2	**135.76**	**136.73**	**5.38**
0.5	**113.69**	**115.32**	**4.54**
1	**99.07**	**101.13**	**3.98**
2	**86**	**88.45**	**3.48**
4	**74.27**	**77.07**	**3.03**
10	**60.48**	**63.69**	**2.51**
20	**51.01**	**54.51**	**2.15**
50	**38.75**	**42.61**	**1.68**
95	**25.99**	**30.23**	**1.19**
99	**22.79**	**27.13**	**1.07**

2010 RAINFALL ESTIMATES			
Percent Chance	Mean Curve	Adjusted Estimates	
Exceedance	mm/day	mm/day	inches/day
10	**66.37**	**69.41**	**2.73**
20	**55.52**	**58.88**	**2.32**
50	**40.28**	**44.10**	**1.74**
95	**22.49**	**26.84**	**1.06**
99	**17.63**	**22.12**	**0.87**

2020 RAINFALL ESTIMATES			
Percent Chance	Mean Curve	Adjusted Estimates	
Exceedance	mm/day	mm/day	inches/day
10	**72.75**	**75.60**	**2.98**
20	**60.77**	**63.97**	**2.52**
50	**43.35**	**47.07**	**1.85**
95	**22**	**26.36**	**1.04**
99	**15.96**	**20.50**	**0.81**

2022 RAINFALL ESTIMATES			
Percent Chance	Mean Curve	Adjusted Estimates	
Exceedance	mm/day	mm/day	inches/day
10	**73.27**	**76.10**	**3.00**
20	**61.47**	**64.65**	**2.55**
50	**44.19**	**47.89**	**1.89**
95	**22.81**	**27.15**	**1.07**
99	**16.72**	**21.24**	**0.84**

2100 RAINFALL ESTIMATES			
Percent Chance	Mean Curve	Adjusted Estimates	
Exceedance	mm/day	mm/day	inches/day
0.2	**134.2**	**135.22**	**5.32**
0.5	**119.44**	**120.90**	**4.76**
1	**108.57**	**110.35**	**4.34**
2	**97.94**	**100.04**	**3.94**
4	**84.18**	**86.69**	**3.41**
10	**73.87**	**76.68**	**3.02**
20	**63.41**	**66.54**	**2.62**
50	**48.14**	**51.72**	**2.04**
95	**29.35**	**33.49**	**1.32**
99	**24.02**	**28.32**	**1.11**

APPENDIX C: US DEPARTMENT OF ENERGY RFI RESPONSES

The questions and responses to the US Department of Energy's questions outlined below. The US Department of Energy's questions are divided into sections on facilities and assets of concern; variables of interest; and data and research needs.

Facilities and assets of concern

Question 1: Could you provide a high-level description about the objective, type, size, and service area of your organization? Please also provide a brief description about the facilities and assets of concern regarding the potential impacts due to climate change (e.g., reservoirs, power plants, transmission lines, conveyance structures, and other energy-water infrastructures)?

Response:

AtkinsRéalis is a global fully integrated engineering services and project management company and is made up of over 50,000 employees in about 130 countries across the globe. AtkinsRéalis offers consulting, design, engineering, construction, capital management and operations services to its clients. Water and infrastructure resiliency is one of our key service areas and we often use climate change information in designing flood control infrastructure, reservoir yield analysis, flood and drought forecasting and transportation corridor resiliency studies. We are also contractors of the Federal Emergency Management Agency (FEMA) and perform floodplain modeling and mapping for FEMA to identify areas that are prone to flood hazard. Rainfall data, streamflow data, and land use data are all inputs to the floodplain modeling work.

Question 2: Could you please describe the customer body, composition, and energy demand that these facilities are supporting?

Response:

Question not applicable to my field of practice.

Question 3: Considering your facilities and assets, what are the potential risks due to climate change? Examples may include but are not limited to floods, droughts, heat waves, wildfires, etc.

Response:

Flood pose significant risk to the infrastructure that Atkins designs for its clients so a changing climate that alters flooding patterns is a risk. The floodplain modeling and mapping we do for FEMA assume that the climate is stationary. A changing climate implies that the assumption of stationarity is incorrect. Hence this requires us to develop a new approach to our analysis that accounts for climate change.

Question 4: For these risks of concern, what worrisome trends in recent decades, if any, have you observed and how have they influenced your facilities and operations?

Response:

Over the past few years, we have observed rare flooding events occur back-to-back. For example, Hurricane Matthew in October 2016 resulted in flooding in the City of Lumberton, NC that up until now was assumed to occur every 200yrs. Two years later, in September 2018, Hurricane Florence also resulted in flooding that was also assumed to occur every 200yrs. This led to overtopping of the Lumberton levee system, which was designed to protect against the 100-year flood, resulting in flooding and destruction of property. This is statistically not possible if the climate was stationary and considerably reduces the effectiveness of our flood control infrastructure.

Question 5: What are other non-climatic risks of concerns and/or trends that you have observed that may affect your long-term operations? Examples may include but are not limited to changing population, energy demand, or urbanization.

Response:

Urbanization is a non-climate risk that is also of concern. Urbanization results in more impervious areas which leads to higher runoff amounts and peaks. Uncertainty in urbanization results in uncertainty in our design of flood control infrastructure.

Variables of interest

Question 6: What meteorologic and hydrologic variables are you using, if any, to support your operations, decision-making, or long-term planning? Examples may include but are not limited to rainfall, temperature, streamflow, snow water equivalent, reservoir storage, groundwater heights, etc.

Response:

AtkinsRéalis mainly uses data on rainfall, temperature, and streamflow in our analysis and design of infrastructure. We also sometimes require reservoir storage and groundwater levels in our analysis.

Question 7: For these variables, what temporal (e.g., sub-daily, daily, weekly, monthly, seasonal, *annual, decadal) and spatial (e.g., point measurement, or regional aggregation by watershed, county, state, or other geographical units) scales are you using to support your operations, decision-making, or long-term planning?*

Response:

Rainfall, temperature, and streamflow data is usually needed in 15-minute intervals for modeling. These data are also required on annual timescales for statistical analysis. Data in weekly, monthly and decadal timescales ae also useful in the determination of trends. Spatially, these data are most used on watershed scales, although point data can also be used.

Question 8: For these variables, what metrics (e.g., average, median, 95 percentile, 100- year return level extremes) are you using to support your operations, decision-making, or long-term planning? Also, how are you characterizing uncertainty in these metrics?

Response:

Metrics on extremes such as 10-,25-, 50-, 100-, and 500-year are very useful for streamflow data. For rainfall and temperature data, the average value with the upper and lower confidence limits are most useful.

Data and research needs.

Question 9: Have you ever used climate data to inform your operation and to evaluate potential future risks? Climate data is broadly defined in this RFI as any relevant historic or future hydro-meteorologic information based on observations, model simulations, or paleo-hydrologic information. Examples may include but are not limited to long-term observation of rainfall, *snowpack, and streamflow, climate model projections (raw or downscaled), reconstructed historic paleo streamflow information, etc.*

Response:

Atkins uses climate data in our resiliency studies that are aimed at designing and constructing climate resilient infrastructure. Climate data is usually from Global Circulation Models (GCMs) which are downscaled spatially and temporarily for use in our analysis and design.

Question 10: If your organization has invested or plans to invest in developing climate change-informed data and decision-making capabilities, what is the preferred method of investment? Examples may include but are not limited to developing direct research contracts with a consultant or research institute, hiring in-house expertise, utilizing government supported technical assistance, joining a community-based consortium, etc.

Response:

AtkinsRéalis, through its City Simulator tool, has invested and continues to invest in climate-informed data and decision support capabilities. City Simulator is a GIS-based tool that creates a digital twin of a city, county, state, or region and evolves it over the planning period (e.g., next 30 to 40 years) to quantify future climate change impacts (i.e. Sea Level Rise, Extreme Rainfall etc) and find ways to mitigate and adapt. Agent-based simulation includes avatars of people that live within the studied area, plus agents moving into and out of the area along other highways. Following a baseline analysis of existing conditions, various scenarios can be created in City Simulator to simulate mitigation alternatives within the study area. One of the key advantages of City Simulator is that it allows for leveraging previous investments in data collection and modeling to stand up an operational simulator in a matter of weeks.

It is normal practice for Atkins to develop future extreme rainfall event depths using the Atkins StormCaster algorithm in City Simulator. The algorithm downscales projections of future rainfall provided by an array of ten general circulation models (GCMs) for the UNIPCC RCP 4.5 and RCP 8.5 scenarios.

The downscaling process includes blending future projections of precipitation from multiple general circulation models (GCM) with historical precipitation data to produce an ensemble precipitation forecast. Results from multiple GCMs are used in the ensemble to capture the varying methods used to model how the global atmospheric/terrestrial/oceanic system will respond to future climate change. Each GCM is run with multiple scenarios that are set by the United Nations Intergovernmental Panel on Climate Change (IPCC). Atkins normally uses the median and extreme greenhouse gas (GHG) concentration scenarios (representative concentration pathway (RCP) 4.5 and RCP 8.5). These scenarios represent the likely and worst-case scenarios.

The Markov probabilities are evaluated for each month to reflect seasonal rainfall patterns. The algorithm then marches forward in time from projection start date to projection end date. In each month, the algorithm marches forward daily, using a random number generator and the Markov probabilities to determine if rain occurs. When rain occurs, a storm is extracted from the appropriate library and inserted into the projection. Storms continue to be inserted until the total depth of rainfall in the forecast matches the projected total rainfall for the month.

To reflect future climate, gauge rainfall depths in 15-minute time step are adjusted based on projected Monthly Rainfall and an extrapolation of historical trend in Standard Deviation of rain events. The algorithm measures the trend by estimating the standard deviation of 15-minute observations in 2-year bins over the 30-year historical record. The algorithm extrapolates this trend in the future rainfall projection by modulating the synthesized storms using a uniformly distributed random number generator to inflate/deflate projected rainfall values.

Design storm estimates for the 100-, 200-, and 500-year return period 24-hour storms are then estimated by fitting a Gumbel distribution to a series of annual maximum 24-hour rainfall events in the rainfall projections. The estimates are calculated using a sliding 30-year window with the first window starting in 1991 and the last ending in 2100.

To estimate the uncertainty in the design storms, twenty GCM projections were used in each RCP assessment, reflecting the variability in GCM physical modelling techniques. Further, ten possible realizations of 15-minute time step future storms were generated from each of the twenty GCM projections, resulting in an ensemble 200-realization future projection.

Question 11: If WPTO provided baseline climate data across a set of potential future scenarios, would that be helpful for supporting your long-term planning and risk assessment? Examples of data that WPTO could provide include but are not limited to ensemble downscaled future temperature, rainfall, streamflow, and snowpack projections, estimated future water and energy demands, projected future land use and land cover change, etc.

Response:

Yes, these will be helpful as these are inputs to our analysis. Our approaches are already set-up to take such data as inputs.

Question 12: If WPTO provided baseline climate data across a set of potential future scenarios, what are time horizons of greatest concern (e.g., seasonal-to-sub seasonal, annual, decadal, multi-decadal, and/or till the end of 21st century)? In considering the severity of climate projections, which emissions scenarios are of greatest interest – high, medium, or low?

Response:

The time horizon of greatest concern for us

Question 13: If WPTO expanded climate change research with respect to hydropower operation and resource planning, what research areas would you like to see explored? Examples may include but are not limited to climate change impacts on water management, drought and water availability assessment, environmental impact analysis, infrastructure safety evaluation, and energy deployment model projection.

Response:

Climate change research on infrastructure safety evaluation, impacts on water management, and drought and water availability assessment will be of great interest to AtkinsRéalis.

Question 14: What additional approaches may help your organization better prepare and address the potential impacts of climate change in your long-term planning?

Response:

Policy development may help my organization better prepare and address the potential impacts of climate change in our long-term planning. Without a uniform policy, climate resiliency work has become a patchwork of varying solutions which makes it very difficult to scale-up. Policy development needs to be data-driven and supported by experienced practitioners. Proposed or suggested mitigation strategies should be wholistic to include items such as typical flood storage, nature-based solutions, Green/Gray/Blue infrastructure The guidance will need to blend enough specificity to allow the design community to get projects into the ground, but flexible enough to account for changing science and social advancements. Policies will need to support an Adaptive Management approach and frame the overall strategy.

Question 15: What additional challenges (e.g., communications, stakeholder perception) have you encountered when addressing the issues of climate change- induced risks?

Response:

Communication with the public (non-scientific community) has always been a challenge when addressing issues with climate change induced risks. It is therefore very essential to focus on communication methods that can drive home the urgency of the situation in order to get community buy-in.