

DISSERTATION

LONG-TERM ANALYSIS OF GROUNDWATER DEPLETION IN THE HIGH PLAINS
AQUIFER: HISTORICAL, PREDICTIVE, AND SOLUTIONS

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ABSTRACT

LONG-TERM ANALYSIS OF GROUNDWATER DEPLETION IN THE HIGH PLAINS AQUIFER: HISTORICAL, PREDICTIVE, AND SOLUTIONS

Semi-arid agricultural regions worldwide are heavily dependent on groundwater storage in a handful of large and over-exploited aquifers, such as the High Plains Aquifer (HPA) in the U.S. High Plains Region. The HPA, one of the world's largest freshwater aquifers, serves as the primary source of irrigation water in the High Plains Region. The socioeconomic development in the High Plains Region has come at the expense of significant groundwater depletion in the HPA. The ongoing depletion of the HPA poses risks to livelihoods of rural communities, local ecosystems, and national food security. Addressing this issue necessitates the formulation of groundwater management policies that aim to reduce groundwater extraction, while minimizing associated economic costs over a multi-generational timeframe, all in the context of climate change. To inform the formulation of effective policies, it is crucial to develop a suite of decision support tools that empower local managers and planners to assess the outcomes of various groundwater management policies amidst climate change.

The primary goal of this dissertation is to enhance the capacity to project the future of groundwater systems in semi-arid agricultural areas, particularly within the High Plains Region, as a coupled human-natural system, under various groundwater management schemes in the face of climate change. To achieve this goal, a number of tools were developed that incorporate a

spectrum of modeling approaches, from the increasingly popular data-driven models to the state-of-the-art hydro-economic models.

First, a data-driven modeling framework was developed and tested that is fast to employ and yet provides reliable long-term groundwater level (GWL) forecasts as a function of climatic and anthropogenic factors. The modeling framework utilizes the random forests (RF) technique in combination with ordinary kriging and was tested for the HPA in Finney County, southwest Kansas. The introduction of groundwater withdrawal potential as a new surrogate for pumping intensity empowers the RF model to capture decline in groundwater depletion rate as the system progresses towards aquifer depletion and/or as a result of well retirement policies. The RF model was applied over the period from 2017 to 2099 using 20 downscaled global climate models (GCMs) for two representative concentration pathways (RCPs), RCP4.5 and RCP8.5. The findings indicate that, under status quo management and average climate conditions, the aquifer will no longer be able to sustain irrigated agriculture in most of the county by 2060. Additionally, the difference in climate scenarios will likely shift the aquifer's depletion time frame by up to 15 years in most of the study area. The long-term combined impact of well retirement plans and climate conditions on groundwater depletion trends imply well retirement policies do not lead to sustained groundwater savings.

In the next step, an agent-based hydro-economic model (ABM-MODFLOW) was developed for a portion of the HPA in eastern Colorado and northwest Kansas, with the aim of addressing the current limitations of hydro-economic models. Through interdisciplinary collaboration, each component of the ABM-MODFLOW was particularly designed to meet specific research objectives. Planting and irrigation decisions were simulated in the ABM-MODFLOW using a detailed representation of real-world farmers. Additionally, well capacity was

incorporated as a constraint on irrigation duration. A subsequent thorough validation of the ABM-MODFLOW was conducted to establish its credibility. The validation results indicate satisfactory performance in reproducing historical data and trends. They also reveal the ABM-MODFLOW's superiority over the standalone groundwater model in simulating the groundwater system. The historical simulation outcomes also underscore the impact of soil type on agents' profitability, especially for those with limited irrigation capacities. Overall, the highest profits are earned by agents with high irrigation capacities and fine soils, while the lowest are achieved by those with low irrigation capacities and coarse soils.

Lastly, the ABM-MODFLOW was employed to project the coevolution of human activities, crops, and the groundwater system amidst climate change, both with and without policy interventions. The ABM-MODFLOW simulations involved 32 climate scenarios from 16 downscaled GCMs for two RCPs, RCP4.5 and RCP8.5. Additionally, three groundwater management policy instruments were explored: irrigated land retirement, irrigation well retirement, and authorized pump rate reduction. The simulation outcomes reveal that the groundwater depletion rate decreases over time, primarily due to rising summer temperatures from climate change that limit corn production, a water-intensive crop, in the region. Moreover, these rising temperatures hamper the economic benefits of policies, since the early conserved groundwater is predominantly used for winter wheat irrigation in the later years, a crop with substantially lower irrigation value than corn.

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DEDICATION

*To my wife, Mahshid, and my parents, Nasrin and Ali, for their unconditional love,
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TABLE OF CONTENTS

ABSTRACT	ii
ACKNOWLEDGMENTS	v
DEDICATION	vi
LIST OF TABLES	x
LIST OF FIGURES	xi
CHAPTER 1. INTRODUCTION	1
1.1. Research background	1
1.2. Research objectives	11
1.3. Significance of the dissertation	12
1.4. Organization of the dissertation	14
CHAPTER 2. EMPLOYING MACHINE LEARNING TO QUANTIFY LONG-TERM CLIMATOLOGICAL AND REGULATORY IMPACTS ON GROUNDWATER AVAILABILITY IN INTENSIVELY IRRIGATED REGIONS	17
2.1. Introduction	18
2.2. Materials and Methods	21
2.2.1. Study Area	21
2.2.2. Random Forests Model Development	23
2.2.3. Long-term Groundwater Level Projections	35
2.3. Results and Discussion	39
2.3.1. Random Forests Model Testing and Evaluation	39
2.3.2. Long-term Projections	47
2.4 Summary and Conclusions	59
CHAPTER 3. DETAILS OF THE EASTERN COLORADO-NORTHWEST KANSAS GROUNDWATER MODEL	63
3.1. Introduction	64
3.2. General Information	65
3.3. Model Domain and Administrative Units	68
3.4. Measured Groundwater Level Data	69
3.5. Model Structure	71
3.5.1. Lateral No-flow Boundaries	74
3.5.2. Lateral Flow Boundaries	74
3.5.3. Hydrogeological Properties	76
3.5.4. Groundwater Extraction	82

3.5.5. Evapotranspiration	93
3.5.6. Recharge	94
3.5.7. Surface Water Features	99
3.6. Model Calibration	103
3.7. Sensitivity Analysis	106
3.8. Model Performance Evaluation	109
CHAPTER 4. CAPTURING HUMAN-CROP-GROUNDWATER INTERACTIONS: MODELING REAL-WORLD AGENTS IN AN INTENSIVELY IRRIGATED REGION OF THE U.S. HIGH PLAINS	118
4.1. Introduction.....	119
4.2. Materials and Methods.....	125
4.2.1. Study Area	125
4.2.2. Agronomic Model	127
4.2.3. Economic Model	133
4.2.4. Hydrologic Model	138
4.2.5. Model Integration.....	140
4.3. Results.....	144
4.3.1. Groundwater Withdrawals	145
4.3.2. Groundwater Levels and Stream Baseflows	146
4.3.3. Crop Yields and Irrigation Use	152
4.3.4. Planting Decisions	154
4.3.5. System Dynamics.....	156
4.4. Discussion	160
4.5. Conclusion	163
CHAPTER 5. GROUNDWATER CONSERVATION IN THE FACE OF CLIMATE CHANGE: DYNAMIC HUMAN-CROP-GROUNDWATER INTERACTIONS IN SEMI-ARID REGIONS	165
5.1. Introduction.....	166
5.2. Materials and Methods.....	171
5.2.1. Study Area	171
5.2.2. ABM-MODFLOW	174
5.2.3. Climate Projections.....	182
5.2.4. Management Scenarios	183
5.3. Results.....	186
5.3.1. Agronomic Outcomes	187
5.3.2. Economic Outcomes	194

5.3.3. Hydrologic Outcomes	202
5.3.4. Comparison of Policy Outcomes	207
5.4. Discussion and Conclusion	209
CHAPTER 6. SUMMARY AND FUTURE RESEARCH DIRECTION	215
6.1. Summary and Closing Remarks	215
6.2. Future research directions	222
REFERENCES	224
APPENDIX A.....	238
APPENDIX B	251
APPENDIX C	258

LIST OF TABLES

Table 2.1. Overview of all input variables considered for groundwater level forecasting (GWL) using the random forests (RF) method.....	27
Table 3.1. MODFLOW model temporal discretization.	73
Table 3.2. Calibrated parameters for the General-Head Boundary (GHB) cells.	76
Table 3.3. Calibrated horizontal hydraulic conductivity (K) and specific yield (S_y) values for different lithology classifications.....	82
Table 3.4. Irrigation efficiency and irrigation return flow for different irrigation systems.	91
Table 3.5. Calibrated parameters for precipitation recharge.	97
Table 3.6. Calibrated parameters for surface water features.....	101
Table 3.7. Composite sensitivity values, percentages, and rankings of calibrated parameters..	108
Table 3.8. Models' performance metrics for groundwater levels and their changes.	112
Table 3.9. Models' performance metrics for average stream baseflows in April and October.	114
Table 4.1. Prevalent soil types in groundwater-fed irrigated parcels and their properties.....	130
Table 4.2. Models' performance metrics for groundwater levels and their changes.	149
Table 4.3. Models' performance metrics for average stream baseflows in April and October.	152
Table 5.1. Estimated intercept and slope coefficients from the ordinary least squares (OLS) model, which quantifies the change in net present value (NPV) of profit from 2019 to 2099 per unit land area for individual farmers under each policy scenario, relative to the no-action scenario.	202

LIST OF FIGURES

Figure 2.1. (a) Study area. (b) Groundwater irrigated lands (GW IRR Lands) and irrigation ditches (IRR Ditches). (c) Irrigation ditch companies' service area enclosed with red line and groundwater level (GWL) measurement points.	23
Figure 2.2. Modeling framework.	36
Figure 2.3. (a) Comparison of performance metrics for the RF model along with four other models in the testing period. (b) Box plots of cumulative residuals at the end of the testing period in different models. (c) Box plots of the RF model's discrete residuals in the testing period.	40
Figure 2.4. Performance metrics of the RF model in groundwater level measurement points.	43
Figure 2.5. Comparison of annual decreases in total groundwater (GW) storage projected by the RF model with annual GW use data (Kansas Geological Survey, 2019c). R denotes the correlation coefficient of these two time series.	44
Figure 2.6. Importance of input variables in the RF model. (a) Impurity-based relative importance values. (b) Permutation-based importance values.	45
Figure 2.7. Spatially averaged historical and projected values of the climatic input variables in Finney County.	48
Figure 2.8. (a) Selected groundwater level (GWL) measurement points, aquifer saturated thickness, and active irrigation (IRR) and non-irrigation (Non-IRR) wells in 2017. (b) Saturated thickness projections at the selected GWL measurement points from 2017 to 2099.	50
Figure 2.9. Total groundwater storage in Finney County projected from 2017 to 2099 under various climate scenarios. (a) Long-term groundwater depletion pathway for each climate scenario. (b) Total groundwater storage variations in different climate scenarios.	52
Figure 2.10. Long-term impacts of climatological factors on groundwater availability in Finney County. (a) Gridded data of the ensemble mean of projected saturated thickness values in 2030, 2060, and 2090. (b) Groundwater depletion time frames estimated based on the minimum (GCMs Minimum), ensemble mean (GCMs Mean), and maximum (GCMs Maximum) of projected saturated thickness values in each RCP. (c) Shifts in groundwater depletion time frames as a result of uncertainties in future climate projections.	55
Figure 2.11. (a) Selected groundwater level (GWL) measurement points, 10%-clusters of candidate wells for retirement used to develop different retirement plans, and the kernel density of all retired wells (i.e., 50% retirement plan). (b) Projected saturated thickness values at the selected GWL measurement points and under a combination of six well retirement plans (including no-action scenario) and two climate scenarios (RCP 4.5 ensemble mean and RCP 8.5 ensemble mean) from 2017 to 2099.	57
Figure 2.12. (a) Total groundwater storage in Finney County projected from 2017 to 2099 under a combination of six well retirement plans (including no-action scenario) and two climate scenarios (RCP 4.5 ensemble mean and RCP 8.5 ensemble mean). (b) Total water saving in each retirement scenario computed as a percentage of total groundwater storage at the beginning of the projection period.	59

Figure 3.1. (a) Study area in relation to the High Plains Aquifer and major river basins. (b) MODFLOW model domain with groundwater-irrigated (GW IRR) lands.	66
Figure 3.2. Model domain and administrative units, including Designated Groundwater Basins (DGBs) and Groundwater Management Districts (GWMDs) in CO, Groundwater Management Districts (GMDs) in KS, and Natural Resources Districts (NRDs) in NE.	69
Figure 3.3. Groundwater level observation points within the model domain. (a) Points and the number of their records used for model calibration (from 1946 to 2010). (b) Points and the number of their records used for model testing (from 2010 to 2018).	71
Figure 3.4. MODFLOW model configuration.	72
Figure 3.5. (a) Boreholes used for the estimation of bedrock elevation, horizontal hydraulic conductivity, and specific yield in the MODFLOW model domain and its immediate vicinity. (b) Depth to bedrock from the land surface.	77
Figure 3.6. Graphical illustration of hydrogeological properties calculation as a function of groundwater level (GWL) for different MODFLOW models. (a) Effective horizontal hydraulic conductivity (K) calculation for the steady-state model. (b) Effective K calculation for the transient models. (c) Effective specific yield (S_y) calculation for the transient models.	78
Figure 3.7. Calibrated effective horizontal hydraulic conductivity (K) values in the MODFLOW model cells during different simulation periods.	80
Figure 3.8. Calibrated effective specific yield (S_y) values in the MODFLOW model cells during different simulation periods.	81
Figure 3.9. System condition during the predevelopment period simulated by the steady-state MODFLOW model. (a) Water table elevation. (b) Depth to water table. (c) Aquifer saturated thickness. (d) Groundwater budget (SW and GW are abbreviations that stand for surface water and groundwater, respectively).	83
Figure 3.10. Groundwater development in the MODFLOW model domain (a) All wells that were operational at any point during the simulation period. (b) Number of active wells during the simulation period.	86
Figure 3.11. Comparison of net irrigation requirements ($Inet$) for corn and winter wheat in groundwater irrigated parcels in 2002 (a dry year) and 2009 (a wet year).	89
Figure 3.12. Historical variation of irrigation systems in the MODFLOW model domain. (a). Percentage of irrigated lands using each irrigation system. (b). Percentage of conventional and Low Energy Precision Application (LEPA) center pivot systems in the Kansas region.	92
Figure 3.13. Evapotranspiration (EVT) cells in the MODFLOW model domain.	94
Figure 3.14. (a) Different precipitation recharge zones in the MODFLOW model domain. (b) Calibrated precipitation recharge curves for non-irrigated lands in different recharge zones.	96
Figure 3.15. Surface water features incorporated in the MODFLOW model.	100
Figure 3.16. Scatter plots of measured (or estimated) values versus simulated values by the MODFLOW model during the calibration period. (a) Groundwater levels (GWLs) in the predevelopment period. (b) GWLs from 1946 to 2010. (c) Stream baseflows from 1946 to 2010. (d) GWL changes (computed at a 5-year interval) from 1946 to 2010.	110

Figure 3.17. Hydrographs for various wells and stream gauges, comparing measured (or estimated) data with simulated values from the MODFLOW model. (a) Groundwater levels. (b) Average baseflows for April and October. The bar chart displays the estimated versus simulated baseflows in every stream gauge during the predevelopment period. CMD stands for cubic meters per day.....	116
Figure 3.18. Hydrographs for various wells and stream gauges, comparing measured (or estimated) data with simulated values from the MODFLOW-RS model. Vertical dotted lines separate data before 1984, as results are generated by the MODFLOW model prior to this year. (a) Groundwater levels. (b) Average baseflows for April and October. CMD stands for cubic meters per day.....	117
Figure 4.1. (a) Location of the hydro-economic model domain relative to the High Plains Aquifer and major river basins. (b) Map of the hydro-economic model domain and groundwater-fed irrigated (GW IRR) parcels.....	127
Figure 4.2. Yield and seasonal irrigation use of corn and winter wheat simulated by DSSAT for varying critical plant available water (PAW_c) and irrigation frequency (IFREQ) values. Data averaged across different soil types and weather conditions from 1981 to 2019. Note: 1 tonne/ha of corn is equal to 15.93 bu/ac, 1 tonne/ha of winter wheat to 14.87 bu/ac, and 1 mm to 0.039 in.	132
Figure 4.3. (a) Agents with varying numbers of irrigation wells and parcels. (b) The representation of the expected profit-maximizing agent's behavior in the economic model; PAW_c and IFREQ represent critical plant available water and irrigation frequency, respectively. (c) Feedbacks between agents' decisions and the groundwater system captured by the hydro-economic model.	134
Figure 4.4. Relationship between well capacity (Q) and aquifer saturated thickness (b) at times i and j based on: (a) Well capacity records at the time of well completion, (b) Well capacity records obtained during meter verification and those included in panel a, and (c) Data from panel b without outliers. Note: 1 CMD (cubic meters per day) is equal to 0.1835 GPM (gallons per minute). ..	141
Figure 4.5. Hydro-economic modeling framework; PAW_c and IFREQ represent critical plant available water and irrigation frequency, respectively.	142
Figure 4.6. (a) Distribution of residuals (simulated minus reported values) for annual pumped water from individual irrigation wells during the 2000-2018 period for the ABM-MODFLOW, MODFLOW, and MODFLOW-RS models. (b) Cumulative groundwater budget for each model between 1984 and 2018. Note: RMSE is expressed in 10^3 m^3 and 10^3 m^3 is equal to 0.81 ac-ft.	146
Figure 4.7. Hydrographs for various wells and stream gauges, comparing measured (or estimated) data with simulated values from the ABM-MODFLOW model. Vertical dotted lines separate data before 1984, as results are generated by the standalone MODFLOW model prior to this year. (a) Groundwater levels. (b) Average baseflows for April and October. Note: 1 m is equal to 3.28 ft and 1 CMD (cubic meters per day) to 0.00041 CFS (cubic feet per second).	148
Figure 4.8. Models' performance metrics for individual wells during the 2010-2018 period. Note: 1 m is equal to 3.28 ft.....	151
Figure 4.9. Time series comparing the ABM-MODFLOW model's simulated crop yields with NASS data, averaged over Kit Carson County in Colorado, and Cheyenne and Sherman counties,	

Kansas. Note: Performance metrics span the 1992-2018 period. RMSE is expressed in tonne/ha and 1 tonne/ha of corn is equal to 15.93 bu/ac and 1 tonne/ha of winter wheat to 14.87 bu/ac. 153

Figure 4.10. Planting decisions. (a) Comparison of the ABM-MODFLOW model's simulated irrigated area with Agricultural Census data, aggregated for Kit Carson County in Colorado, and Cheyenne and Sherman counties in Kansas. (b) Percentage distribution of selected crops during the 2008-2017 period, as simulated by the model, alongside estimates derived from NASS Cropland Data Layers combined with remote sensing data (CDL-RS). (c) Time series of planted area with each crop across the study area, as simulated by the model. Note: 1 ha is equal to 2.47 ac. 155

Figure 4.11. (a) Time series of profit distribution for agents with low (less than 62 CMD/ha), medium (between 62 and 91 CMD/ha), and high (greater than 91 CMD/ha) irrigation capacities in 1984. The color of box plots indicates the mean irrigation capacity for each year. (b) Time series of the mean SPEI-3 values during the growing season (May to September). SPEI-3 denotes the standardized precipitation evapotranspiration index with a three-month aggregation period. Note: 1 CMD/ha is equal to 0.074 GMP/ac and 1 USD/ha to 0.405 USD/ac. 157

Figure 4.12. (a) Irrigation capacity in 1984. (b) Generalized soil categories. (c) Average annual profit from 1984 to 2018. (d) Average annual profit from 1984 to 2018 based on combinations of soil type and initial irrigation capacity categories. See Table 4.1 for soil names and properties. Note: 1 CMD/ha is equal to 0.074 GMP/ac and 1 USD/ha to 0.405 USD/ac. 159

Figure 5.1. (a) Study area in relation to the High Plains Aquifer and major river basins. (b) ABM-MODFLOW domain with irrigated (IRR) wells and groundwater-irrigated (GW IRR) parcels in 2018. (c) Heterogeneity among farmers (agents) in terms of well numbers and farm size. 173

Figure 5.2. Representation of the agents' decision-making process within the economic model. PAW_c and IFREQ denote critical plant available water and irrigation frequency, respectively. 177

Figure 5.3. Distributions of the total area planted for each crop in 2032, 2059, and 2086, as projected by the ABM-MODFLOW under an ensemble of climate projections for RCP4.5 and different management scenarios. These three years are the median years of short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099). 189

Figure 5.4. Distributions of the total area planted for each crop in 2032, 2059, and 2086, as projected by the ABM-MODFLOW under an ensemble of climate projections for RCP8.5 and different management scenarios. These three years are the median years of short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099). 190

Figure 5.5. Simulated crop yields using the agronomic model (DSSAT) based on climate projections from an ensemble of global climate models (GCMs) for RCP4.5 and RCP8.5 (top and middle panels). Average daily mean temperature in May (winter wheat flowering stage) and July (corn flowering stage) derived from these GCM projections for the same RCPs (bottom panel). Vertical dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099). Horizontal dotted lines indicate the optimal temperatures (T_{opt}) for winter wheat and corn flowering. 192

Figure 5.6. Region-wide undiscounted annual profits per unit land area as simulated by the ABM-MODFLOW, based on an ensemble of global climate models (GCMs) projections for RCP4.5 under various management scenarios. Annotations within the plots present the Mann-Kendall test results for trend significance, and numbers in parentheses indicate the Sen's slope estimator values

for trend slopes, where significant. Blue annotations correspond to the no-action scenario, while orange annotations pertain to scenarios with policy interventions. Dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).	195
Figure 5.7. Region-wide undiscounted annual profits per unit land area as simulated by the ABM-MODFLOW, based on an ensemble of global climate models (GCMs) projections for RCP8.5 under various management scenarios. Annotations within the plots present the Mann-Kendall test results for trend significance, and numbers in parentheses indicate the Sen's slope estimator values for trend slopes, where significant. Blue annotations correspond to the no-action scenario, while orange annotations pertain to scenarios with policy interventions. Dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).	196
Figure 5.8. Influence of groundwater management policies on farmers' profitability across the region under RCP4.5. (a) Net present value (<i>NPV</i>) of profit per unit land area for individual farmers under the no-action scenario, with <i>NPV</i> calculated as the ensemble mean of simulation outcomes under climate projections from multiple global climate models (GCMs). (b) Percent change in <i>NPV</i> of profit, relative to the no-action scenario, under different groundwater management policies.	199
Figure 5.9. Total groundwater storage in the study area as simulated by the ABM-MODFLOW, based on an ensemble of global climate models (GCMs) projections for RCP4.5 under various management scenarios. Dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).	204
Figure 5.10. Influence of groundwater management policies on the aquifer's saturated thickness across the region under RCP4.5. (a) Saturated thickness in 2099 under the no-action scenario, calculated as the ensemble mean of simulation outcomes under climate projections from multiple global climate models (GCMs). (b) Change in saturated thickness in 2099, relative to the no-action scenario, under different groundwater management policies.	206
Figure 5.11. Comparison of region-wide policy outcomes under RCP4.5. All percent change values are calculated relative to the no-action scenario, based on the ensemble mean of simulation outputs from multiple global climate models (GCMs). <i>NPV</i> stands for net present value.	209

CHAPTER 1.

INTRODUCTION

1.1. Research background

Groundwater, the primary source of unfrozen freshwater on the planet, accounts for 42% of global irrigation water withdrawals, with 18% coming from non-renewable (fossil) groundwater resources (Aeschbach-Hertig and Gleeson, 2012; Döll et al., 2012; Wada et al., 2012). In particular, semi-arid agricultural regions worldwide are heavily dependent on groundwater storage in a handful of large and over-exploited aquifers, such as the High Plains and Central Valley in the United States, the North China Plain in China, and the Indus-Upper Ganges in India and Pakistan (Aeschbach-Hertig and Gleeson, 2012; Gleeson et al., 2012b; MacDonald et al., 2016). Continuous depletion of these aquifers jeopardizes not only the livelihoods of rural communities dependent on irrigated agriculture for income and employment (Lauer et al., 2018), but also imperils global food security given the rising food demand driven by population growth and changing diets (Aeschbach-Hertig and Gleeson, 2012; Famiglietti, 2014). Moreover, groundwater depletion is expected to intensify in these areas amidst climate change due to likely increases in irrigation requirements and a growing reliance on groundwater over surface water for irrigation (Cook et al., 2015; Liu et al., 2022; Taylor et al., 2013).

The High Plains Aquifer (HPA), one of the world's largest freshwater aquifers (Gowda et al., 2019; Haacker et al., 2019), spans approximately 452,600 km² in the U.S. High Plains Region, covering portions of eight states: Colorado, Kansas, Nebraska, New Mexico, Oklahoma, South Dakota, Texas, and Wyoming. The Miocene Ogallala Formation is the dominant constituent of the HPA with about 77% areal coverage (Gutentag et al., 1984), which holds the bulk of groundwater,

generally in unconfined condition. Hence, the HPA is also frequently referred to as the Ogallala Aquifer. The formation of the Ogallala can be tracked back to sediments eroded from alluvial fans fronting the modern Rocky Mountains, which were then transported by streams flowing towards the Great Plains (Topper et al., 2003).

The HPA is the primary source of irrigation water in the High Plains Region, which accounts for more than 11% of the U.S. agricultural market value (Scanlon et al., 2012). During the 1920s, as agriculture expanded in the High Plains Region, many native drought-resistant grasslands were converted to drought-sensitive croplands (Cook et al., 2009). Prolonged droughts and subsequent failures in dryland agricultural practices led to the Dust Bowl of the 1930s. This catastrophe left fields uncultivated and the dry, friable topsoil exposed to wind erosion. Lessons from the Dust Bowl prompted farmers to adopt new management practices, including the widespread use of groundwater for irrigation starting the 1950s (Basso et al., 2013). In fact, this shift towards irrigation and soil conservation strategies has not only sustained the High Plains Region's economic prosperity but also reduced soil erosion and prevented dust storms.

The socioeconomic development in the High Plains Region, however, has come at the expense of significant groundwater depletion in the HPA, which exhibits the highest average depletion rate among major aquifer systems in the U.S. (Konikow, 2015). Research indicates that, given the current extraction rates, parts of the aquifer in the Southern and Central High Plains as well as southwestern areas of the Northern High Plains will no longer support irrigated agriculture in the upcoming decades (Scanlon et al., 2012; Steward et al., 2013; Haacker et al., 2016; Deines et al., 2020). The depletion of groundwater in the HPA has cascading effects on the economy, society, and environment, leading to increased pumping costs, diminished well capacities (yields), decline in employment and population in rural communities, streamflow depletion, and an elevated

risk of dust storms as irrigated agriculture ceases (Aistrup et al., 2017; Dennehy et al., 2002; Scanlon et al., 2012; Steward et al., 2013). Compounding this challenge, climate projections suggest the High Plains Region will face substantially drier conditions in the latter half of the 21st century (Cook et al., 2015; Harding and Snyder, 2012), which could amplify irrigation demands and expedite groundwater depletion (Cotterman et al., 2018). An effective approach for managing this complex situation could be to implement groundwater management policies that reduce irrigation water demand, prolong the HPA's lifespan, and sustain stream baseflows (Whittemore et al., 2023).

Federal and state agencies, along with local groundwater management districts, are keen to assess the combined impacts of groundwater management strategies and climate change on future groundwater levels (GWLs) and depletion timelines in the HPA. To address this need, it is crucial to develop tools capable of rapidly forecasting long-term GWLs based on climatic and anthropogenic factors at a regional scale. Data-driven statistical groundwater models are emerging as prominent tools in this context. Unlike physically-based groundwater models, which simulate groundwater storage and flow through solving mass balance equations, data-driven models leverage soft computing and machine learning (ML) techniques (Solomatine and Ostfeld, 2008; Amaranto et al., 2018). These models identify nonlinear hidden patterns in historical data, using them to predict future GWLs without imposing any rules for underlying physical processes (Sahoo et al., 2017). Therefore, they offer a suitable alternative to traditional physically-based models (Daliakopoulos et al., 2005; Adamowski and Chan, 2011).

In the past two decades, there has been a notable rise in studies using ML methods for GWL modeling, attributed to their ease of application, relatively short run time, and suitable performance. Among the various ML and soft computing techniques for groundwater modeling,

prominent ones include artificial neural network (ANN) (Guo et al., 2021; Anshuman and Eldho, 2022; Hakim et al., 2022; Nourani et al., 2022b), extreme learning machine (ELM) (Alizamir et al., 2018; Natarajan and Sudheer, 2020), genetic programming (GP) (Shiri and Kişi, 2011; Fallah-Mehdipour et al., 2013), and support vector machine (SVM) (Yoon et al., 2011; Guzman et al., 2019; Mohapatra et al., 2021). Beyond these commonly used methods, the application of ensemble learning algorithms such as random forests (RF) (Amaranto et al., 2018; Sahoo et al., 2018; Wang et al., 2018; Koch et al., 2019), gradient boosting machine (GBM) (Sharafati et al., 2020), and extreme gradient boosting (XGB) (Rahman et al., 2020) has gained traction in recent years.

While there has been a recent surge in the number of studies focused on the development and testing of data-driven models for precise GWL forecasting at monthly or finer time scales (Rajaei et al., 2019), only a few studies have explored the application of such models for long-term GWL predictions or estimating groundwater depletion time frames (Haacker et al., 2016; Steward and Allen, 2016; Salem et al., 2018). However, these existing efforts often overlook exogenous factors (e.g., climate conditions) that influence future GWLs, or they deal with groundwater depletion rates that are substantially lower than those seen in the HPA. Additionally, only a handful of studies to date have evaluated the potential impacts of groundwater management policies on GWLs using data-driven models (Feng et al., 2008) or semi-statistical water balance approaches (Butler et al., 2020a). A comprehensive review of the literature indicates that ML has yet to be employed to assess the long-term impacts of these policies on groundwater resources in the face of climate change.

While data-driven models serve as rapid assessment tools, it is essential to note that human activities are the primary cause of the imbalance between groundwater recharge and extraction in intensively irrigated regions. Thus, addressing the groundwater depletion issue in these regions

without considering economic factors would be impractical. From an economic standpoint, groundwater depletion is rooted in its nature as a common property resource. This results in the “tragedy of the commons”, where individual users excessively exploit the shared groundwater with no incentive to limit their extraction to socially optimal levels, ultimately leading to a market failure (Aeschbach-Hertig and Gleeson, 2012; Rouhi Rad et al., 2020b; Steward et al., 2013). Within this context, addressing groundwater depletion requires the implementation of policy instruments that both extend the aquifer’s lifespan and minimize the economic costs associated with reduced water use (Hrozencik et al., 2017).

Hydro-economic models serve as cutting-edge tools for evaluating water management policies, including those focused on groundwater, at a regional scale (Kahil et al., 2016). These models integrate neoclassical economics with hydrology, and often agronomy, providing a coherent modeling framework (Harou et al., 2009). Over the past four decades, there has been extensive research using hydro-economic models to assess the costs and benefits of groundwater management policies (Aistrup et al., 2017; Brill and Burness, 1994; Gisser and Sánchez, 1980).

In recent hydro-economic modeling literature on groundwater systems, a variety of groundwater management schemes and policy instruments have been evaluated. Some studies compare welfare gains from centralized optimal control to those from decentralized scenarios, wherein individual farmers aim to maximize their profits either autonomously or under policy instruments like uniform taxes or quantity restrictions (Guilfoos et al., 2013; Mulligan et al., 2014). Guilfoos et al. (2016) examine a wide range of policy instruments, including tax and quantity restrictions as well as groundwater markets (i.e., trading water rights for groundwater extraction while maintaining the total extraction restricted) implemented at both aquifer-wide and local scales. Hrozencik et al. (2017) analyze the heterogeneous impacts of uniform policy instruments,

such as pumping fees, quantity restrictions, and irrigated acreage fees, on farmers within a river basin. Khan & Brown (2019) compare the performance of groundwater markets with quantity restriction policy instruments under different future climate conditions, while Manning et al. (2020) assess the economic benefits of a groundwater right retirement program for farmers. While these studies provide valuable insights, the hydro-economic models they employ often have certain structural limitations, potentially affecting their reliability.

In hydro-economic modeling of groundwater systems, the groundwater model plays a pivotal role in policy evaluation. This is because the effectiveness of a policy hinges on GWL variations in irrigation wells and the responsiveness (elasticity) of crop production and revenue to those changes (Manning and Suter, 2019). However, previous studies have often undervalued the significance of using appropriate groundwater models. Brozović et al. (2010) demonstrated that hydro-economic models which employ a lumped groundwater model with infinite hydraulic conductivity (commonly referred to as a “bathtub” model) are prone to the underestimation of pumping externalities and groundwater management benefits. In response to their findings, several later studies began incorporating a spatially distributed representation of groundwater systems into their hydro-economic models.

Some of these studies have developed custom-made groundwater models, applying Darcy’s Law and mass balance equations directly to simulate groundwater flow and storage (Guilfoos et al., 2016, 2013; Kahil et al., 2016). Despite explicitly modeling groundwater flow and storage, these models exhibit various oversimplifications that could undermine the reliability of the corresponding hydro-economic models.

Several other studies have utilized pre-existing regional MODFLOW models (Harbaugh et al., 2000) that were initially developed for purposes other than hydro-economic modeling

(Hrozencik et al., 2017; Hu et al., 2015; Khan & Brown, 2019; Mulligan et al., 2014; Noël & Cai, 2017; Rouhi Rad et al., 2020b). Although using pre-existing groundwater models simplifies the development of hydro-economic models, it is important to recognize that these models do not offer full control over groundwater extraction in individual irrigation wells or groundwater recharge in the associated irrigated parcels. Specifically, all of these studies fail to consider the effect of changes in irrigated area on precipitation recharge, despite the fact that irrigation enhances precipitation recharge by increasing soil moisture (Cherry et al., 2020). A previous modeling study in a semi-arid region estimated that annual precipitation recharge in irrigated lands is amplified by a factor of 2.0 (Liu et al., 2010).

Furthermore, some studies do not compute irrigation return recharge with respect to irrigation amounts, instead defaulting to initially specified values in the models (Hrozencik et al., 2017; Hu et al., 2015; Rouhi Rad et al., 2020b). Previous modeling studies in semi-arid regions indicate that as much as 25% of the total water pumped for irrigation could return to the saturated zone as recharge, depending on the irrigation system (Liu et al., 2010; Republican River Compact Administration, 2003). Thus, having complete control over components of the groundwater budget is crucial, since hydro-economic simulations may involve shifts in land use, from irrigated to dryland crops and vice versa, which in turn can influence both groundwater extraction and recharge. The overestimation (underestimation) of groundwater recharge would subsequently lead to the underestimation (overestimation) of groundwater depletion costs and groundwater management benefits.

Apart from the hydrologic component, the reliability and applicability of hydro-economic models heavily depend on the accurate representation of water users. In hydro-economic models, if decision-making units represent individual water users instead of a centralized planner, the

economic component can be classified as an agent-based model (ABM). In regions where groundwater-fed irrigation is dominant, the agents are farmers using groundwater for irrigation. These agents make decisions on the entirety of their farm, considering characteristics of their irrigation well(s), such as well capacity, and attributes of the parcel(s) in their farm, including size and soil type. Notably, existing research underscores that farm size shapes the planting and irrigation decisions of each agent, and is likely a determinant of gains from groundwater management (Saak and Peterson, 2012).

Previous studies, however, have overlooked incorporating agents that represent their real-world counterparts. Many studies have created agents by clustering individual wells using model reduction techniques (Khan and Brown, 2019; Mulligan et al., 2014), aggregating individual wells within the same groundwater model cell (Guilfoos et al., 2016, 2013; Noël and Cai, 2017), or defining them based on political or regulatory boundaries (Aistrup et al., 2017; Hu et al., 2015; Lei et al., 2019). In some instances, agents are represented by individual wells with a uniform parcel size (Hrozencik et al., 2017; Rouhi Rad et al., 2020b). Such approaches fail to capture the significant heterogeneity that exists among agents at the regional scale and can miscalculate the path and the costs of groundwater depletion.

In hydro-economic models, agents' decisions are significantly influenced by declining well capacity, a major concern recognized by groundwater management organizations in the U.S. (Hrozencik et al., 2023). Well capacity refers to the maximum rate of groundwater extraction from a well without causing it to run dry. With declining well capacity, irrigation application rates become restricted, leading to considerable reductions in irrigated area, seasonal irrigation use, and profit (Foster et al., 2014). Diminished well capacity results in longer duration of irrigation applications, exposing crops to extended periods without irrigation and potentially elevated water

stress. Failing to explicitly account for this constraint associated with irrigation application durations can produce inaccurate predictions of crop yield, irrigation use, and profitability (Domínguez et al., 2022). This may lead to the underestimations of both the costs of groundwater depletion and the benefits of groundwater management. Nevertheless, the impact of well capacity on irrigation durations has received limited attention in previous hydro-economic modeling studies.

In hydro-economic models, the agronomic component is pivotal in simulating agents' decisions by generating crop-water production functions that link water use to crop yield. While recent studies have recognized the value of incorporating crop simulation models as advanced tools for developing stochastic crop-water production functions (Foster et al., 2014; Hrozencik et al., 2017), only one study has leveraged these models to simulate both preseason planting and irrigation decisions of farmers within a stochastic framework, taking into account uncertainties in weather conditions during the growing season (Rouhi Rad et al., 2020b).

In addition to the factors mentioned earlier that influence the performance of hydro-economic models, a thorough evaluation of their performance is essential yet challenging, similar to other integrated models (Haacker et al., 2019; Voinov and Shugart, 2013). The credibility and acceptance of hydro-economic models among stakeholders heavily depend on their ability to sufficiently reproduce historical data (Harou et al., 2009). Employing hydro-economic models for policy analysis without a robust performance evaluation casts doubt about the reliability of the outcomes and subsequent policy implications. However, previous hydro-economic models of groundwater systems have not been extensively validated against observed data. Although a few of these models have undergone partial testing (Aistrup et al., 2017; Guilfoos et al., 2016; Mulligan et al., 2014; Noël and Cai, 2017), their evaluation was not comprehensive.

Groundwater sustainability, with its multi-generational timeframe spanning 50 to 100 years (Gleeson et al., 2012a), must be viewed in the context of human-induced climate change. Climate change can affect groundwater systems directly through variations in groundwater evapotranspiration (ET) and recharge rates and/or indirectly through changes in groundwater extraction and land-use prompted by human activities (Scanlon et al., 2021; Taylor et al., 2013). Variations in groundwater extraction predominantly stem from shifts in irrigation demands and the sources of irrigation water. Land-use change can both enhance precipitation recharge in irrigated lands due to increased soil moisture and alter irrigation demands as crop selections change. In semi-arid agricultural regions, where groundwater is relatively deep and extensively pumped for irrigation, the indirect impacts of climate change on groundwater systems are likely to dominate direct ones (Russo and Lall, 2017).

The existing hydrologic modeling literature, however, predominantly focuses on the direct impacts, particularly variations in recharge (Crosbie et al., 2011; Cuthbert et al., 2019; Niraula et al., 2017). While some recent studies explore the indirect impacts (Chen et al., 2023; Kumar et al., 2023; Ou et al., 2018), they fail to account for potential shifts in farmers' crop choices and irrigation strategies driven by groundwater availability and climate-induced changes in crop profitability. Moreover, these studies do not consider any groundwater management policies in their analysis. Among them, only Kumar et al. (2023) utilize a crop simulation model to thoroughly investigate the effects of climate change on crop water demands, particularly the enhancing impacts of elevated atmospheric carbon dioxide concentrations (CO₂) on crop water productivity (Deryng et al., 2016).

Since hydro-economic models account for the interplay between climate, crops, human activities, and groundwater, they can be employed as valuable tools for simulating the indirect

impacts of climate change on groundwater systems under both no-action (status quo) and policy scenarios. However, they have yet to be employed to study the effects of climate change on groundwater systems using a scenario-based approach. In numerous prior hydro-economic modeling studies, future climate conditions are either assumed constant (Mulligan et al., 2014) or treated by repeating a historical weather cycle (Hrozencik et al., 2017; Manning et al., 2020; Rouhi Rad et al., 2020b). One study considers climate change by weighting historical weather data, making drier than average years progressively more probable (Aistrup et al., 2017). In another study, climate change is incorporated by perturbing historical climate data based on future climate projections, but without a crop simulation model, it assumes that crop water needs change linearly with temperature (Khan and Brown, 2019). Notably, none of the previous studies account for the influence of increased CO₂ on crop yields and water use, and consequently on the crop-water production functions.

1.2. Research objectives

The primary goal of this dissertation is to enhance the capacity to project the future of groundwater systems in semi-arid agricultural areas, as a coupled human-natural system, under various groundwater management schemes in the face of climate change. To achieve this goal, a number of tools were developed that incorporate a spectrum of modeling approaches, from the increasingly popular data-driven models to the state-of-the-art hydro-economic models. Specifically, the objectives were to:

1. Develop and evaluate a data-driven modeling architecture (random forests-kriging) for long-term groundwater level forecasting in groundwater-fed irrigated regions under different climate and regulatory conditions.

2. Develop, calibrate, and validate a groundwater model (MODFLOW) for a portion of the High Plains Aquifer (HPA) in eastern Colorado and northwest Kansas, aiming to seamlessly integrate it with field-scale agronomic and economic models within a hydro-economic modeling framework that requires full control over groundwater extraction in individual irrigation wells and recharge in the associated irrigated parcels.

3. Develop and rigorously validate an agent-based hydro-economic model (ABM-MODFLOW) by integrating the developed MODFLOW model with agronomic and economic models, aiming to address the common limitations identified in previous hydro-economic models.

4. Project the coevolution of human activities, crops, and groundwater in semi-arid agricultural regions amidst climate change, both with and without groundwater management, by employing the ABM-MODFLOW.

Meeting these research objectives yields a suite of decision-support tools developed to inform the future of groundwater systems in semi-arid agricultural regions under different climate and management conditions. These tools will assist stakeholders in formulating effective groundwater management policies. By implementing such policies, it is possible to decrease irrigation water demand, extend the lifespan of aquifers, and sustain stream baseflows, while minimizing the economic costs of reduced water usage for farmers.

1.3. Significance of the dissertation

This dissertation makes several significant contributions to the literature on modeling groundwater systems in semi-arid agricultural regions. First, it introduces a data-driven modeling framework (random forests-kriging), specifically designed for long-term forecasting of groundwater levels based on both climatological and anthropogenic factors. Notably, a new input

variable named groundwater withdrawal potential is introduced, which is the product of aquifer saturated thickness and number of active high production wells, as a proxy for unavailable pumping data in long-term groundwater level projections. Moreover, random forests-kriging is distinctive in being the first data-driven groundwater modeling framework that can incorporate a groundwater management policy instrument into its forecasts. The proposed modeling framework can serve as a rapid assessment tool, informing stakeholders about future groundwater availability at the regional scale, and helping them to determine the urgency of adaptation and/or conservation strategies. While the modeling framework is tested for the High Plains Aquifer (HPA) in Finney County, southwest Kansas, its applicability extends to other heavily stressed aquifers in semi-arid agricultural regions worldwide.

Second, the modeling components of the agent-based hydro-economic model (ABM-MODFLOW) in this dissertation are specifically constructed through interdisciplinary collaboration, with the explicit aim of integrating them into a hydro-economic modeling framework. This unique feature enables the ABM-MODFLOW to overcome common limitations observed in previous hydro-economic modeling efforts. Specifically, the decision-making units (agents) in the ABM-MODFLOW closely represent their real-world counterparts, making the model more applicable and realistic. Additionally, the ABM-MODFLOW takes into account well capacity and its effect on the duration of irrigation applications as a significant factor affecting agents' planting and irrigation decisions. Furthermore, the comprehensive validation of the ABM-MODFLOW against observed data not only establishes its credibility but also highlights the suitability of our methodology for modeling heavily stressed groundwater systems in semi-arid regions affected by human activities.

Third, this dissertation pioneers the employment of a rigorously validated hydro-economic model (ABM-MODFLOW) to study the joint impacts of climate change and groundwater management on groundwater systems using a scenario-based approach. Through the ABM-MODFLOW, the research underscores the indirect effects of climate change, notably elevated atmospheric carbon dioxide concentrations (CO_2), on groundwater systems. It also illustrates the intertwined effects of groundwater depletion and climate change on crop production and farmers' profitability. Although the ABM-MODFLOW simulations are conducted on a regional scale and the primary objective of these simulations is not to formulate effective policies per se, the exploration of system dynamics under various climatic and regulatory conditions provides valuable insights and policy implications for enhancing groundwater management in semi-arid agricultural regions worldwide.

1.4. Organization of the dissertation

This dissertation is organized into six chapters as follows:

Chapter 1: Provides a comprehensive research background, main objectives, and significance of the dissertation.

Chapter 2: Develops a data-driven model for long-term groundwater level forecasts as a function of climatological and anthropogenic factors. This model integrates the random forests (RF) technique with ordinary kriging, and is tested for the High Plains Aquifer (HPA) in Finney County, southwest Kansas. Predictions span from 2017 to 2099 across 40 climate scenarios, derived from 20 downscaled global climate models (GCMs) for two representative concentration pathways (RCPs), RCP4.5 and RCP8.5. In addition to these climate scenarios, six management scenarios are considered in this chapter, including a no-action (status quo) scenario and five

distinct well retirement plans, ranging from 10% to 50% random retirement of active irrigation wells over a 10-year period from 2021 to 2030.

Chapter 3: Explains the details of a groundwater model (MODFLOW) developed for a portion of the High Plains Aquifer (HPA) in eastern Colorado and northwest Kansas. The simulation period of the MODFLOW model is divided into two periods: the steady-state predevelopment period, representing the time before May 1st, 1946, and the transient post-development period, covering May 1st, 1946 to September 30th, 2018. The MODFLOW model is calibrated by adjusting a total of 49 parameters using measured groundwater levels and estimated stream baseflows. This chapter also introduces a modified version of the model, MODFLOW-RS, which leverages remote sensing data to estimate groundwater extraction for irrigation purposes.

Chapter 4: Develops an agent-based hydro-economic model (ABM-MODFLOW) for an intensively groundwater-fed irrigated region overlying the High Plains Aquifer (HPA) in eastern Colorado and northwest Kansas. It integrates the MODFLOW model, developed, calibrated, and validated in Chapter 3, with field-scale agronomic (DSSAT) and economic models. The ABM-MODFLOW is validated against several categories of observed data from 1984 to 2018. Moreover, its performance is compared with both the standalone MODFLOW and MODFLOW-RS models.

Chapter 5: Employs the ABM-MODFLOW, developed and validated in Chapter 4, to simulate the coevolution of human activities, crops, and the groundwater system under various climate and management scenarios from 2019 to 2099. A total of 32 climate scenarios are considered based on downscaled projections from 16 global climate models (GCMs) for two representative concentration pathways (RCPs), RCP4.5 and RCP8.5. The simulations also include 10 management scenarios: a no-action (status quo) scenario, three irrigated land retirement

scenarios, three irrigation well retirement scenarios, and three authorized pump rate reduction scenarios that differ in their intensity.

Chapter 6: Provides a summary of the dissertation, highlights the key findings, and suggests directions for future studies.

CHAPTER 2.
EMPLOYING MACHINE LEARNING TO QUANTIFY LONG-TERM CLIMATOLOGICAL
AND REGULATORY IMPACTS ON GROUNDWATER AVAILABILITY IN
INTENSIVELY IRRIGATED REGIONS ¹

Highlights

The steady overexploitation of the Ogallala Aquifer underlying the U.S. High Plains Region has put irrigated crop production at risk, particularly in the Southern and Central High Plains. To manage this issue properly, a data-driven modeling framework is developed and tested that is fast to employ and yet provides reliable long-term groundwater level (GWL) forecasts as a function of climatological and anthropogenic factors. The modeling framework uses the random forests (RF) technique in combination with ordinary kriging, and is tested in Finney County in southwest Kansas. The introduction of groundwater withdrawal potential as a new surrogate for pumping intensity enables the RF model to capture decline in groundwater depletion rate as the system progresses towards aquifer depletion and/or as a result of well retirement policies. The RF model is executed from 2017 to 2099 for 20 different downscaled global climate models (GCMs) for the two representative concentration pathways (RCP) scenarios of 4.5 and 8.5. The results show the aquifer will cease to support irrigated agriculture in most of the county by 2060 under status quo management and average climate conditions. Moreover, climate will likely shift the aquifer's depletion time frame by 15 years or less in most of the study area. The long-term combined impact of well retirement plans and climate conditions on groundwater depletion trends imply well

¹ This chapter has been published as a journal article titled “Employing machine learning to quantify long-term climatological and regulatory impacts on groundwater availability in intensively irrigated regions” in the Journal of Hydrology, Volume 614, Part A, November 2022, 128511.

retirement policies do not lead to sustained groundwater savings. This study demonstrates the capacity of machine learning models to serve as a rapid assessment tool, informing policymakers about future groundwater availability in intensively irrigated regions and under different climate and management conditions.

2.1. Introduction

Many critical aquifers for irrigated agriculture are undergoing unsustainable depletion (Gleeson et al., 2012b; Konikow, 2015). The Ogallala Aquifer, which consists of the Neogene period Ogallala Formation, is the dominant constituent of the High Plains Aquifer System with about 77% areal coverage of the whole system (Gutentag et al., 1984) and is known as one of the largest and most heavily utilized freshwater aquifers worldwide (Gowda et al., 2019; Haacker et al., 2019). In the Ogallala Aquifer, groundwater is generally under unconfined conditions and crop and livestock production in the U.S. High Plains Region rely heavily on this exhaustible resource (Steward et al., 2013; Gowda et al., 2019).

The Ogallala Aquifer has been undergoing depletion since at least the middle of the 20th century (Gutentag et al., 1984; Scanlon et al., 2012; McGuire, 2017) and with current rates of extraction, portions of the aquifer in the Southern and Central High Plains will cease to support irrigated agriculture within the next few decades (Scanlon et al., 2012; Steward et al., 2013; Haacker et al., 2016; Deines et al., 2020). Compounding this challenge, drought severity, frequency, and persistence are expected to increase with climate change throughout the High Plains Region (Harding and Snyder, 2012), amplifying groundwater demand to support crop production and likely shortening the timeline to depletion (Cotterman et al., 2018). On the other hand, the implementation of management strategies such as pumping reduction and water rights retirement could possibly extend the aquifer lifespan (Butler et al., 2016; Manning et al., 2020).

To manage this complex situation, federal and state organizations as well as local groundwater management districts are interested in the possible impacts of climate change and conservation policies on future water levels and depletion time frames across the Ogallala Aquifer. Developing a tool capable of rapid long-term forecasting of groundwater levels (GWLs) as a function of climatological and anthropogenic factors at the regional scale (i.e., county level) is an important step.

Forecasting tools include both physically based hydrologic models and data-driven statistical models. In contrast to physically based models that solve governing mass balance equations to simulate groundwater storage and flow in aquifer system, data-driven models use soft computing and machine learning (ML) techniques (Solomatine and Ostfeld, 2008; Amaranto et al., 2018). These techniques capture nonlinear hidden patterns in historical data and use those patterns to forecast future GWLs in aquifers without imposing rules for any underlying physical processes (Sahoo et al., 2017) and can be a suitable alternative to physically based models (Daliakopoulos et al., 2005; Adamowski and Chan, 2011).

Over the last two decades the number of studies using ML methods in GWL modeling has steadily increased due to their ease of application and relatively short run time, along with desirable performance. Among different ML and soft computing techniques in groundwater modeling, some of the more commonly used ones are artificial neural network (ANN) (Guo et al., 2021; Anshuman and Eldho, 2022; Hakim et al., 2022; Nourani et al., 2022b), extreme learning machine (ELM) (Alizamir et al., 2018; Natarajan and Sudheer, 2020), genetic programming (GP) (Shiri and Kişi, 2011; Fallah-Mehdipour et al., 2013), and support vector machine (SVM) (Yoon et al., 2011; Guzman et al., 2019; Mohapatra et al., 2021). In addition to the widely used methods in GWL modeling, the application of ensemble learning algorithms such as random forests (RF) (Amaranto

et al., 2018; Sahoo et al., 2018; Wang et al., 2018; Koch et al., 2019), gradient boosting machine (GBM) (Sharafati et al., 2020), and extreme gradient boosting (XGB) (Rahman et al., 2020) has become more popular in recent years.

While the number of studies regarding development and testing data-driven models for accurate GWL forecasting at a monthly or sub-monthly time step has increased in recent years (Rajaei et al., 2019), only a few studies have attempted to utilize such models for either long-term GWL prediction or the projection of groundwater depletion time frame (Haacker et al., 2016; Steward and Allen, 2016; Salem et al., 2018). However, these existing studies either ignored the exogenous factors (e.g., climate condition) affecting future GWLs or groundwater depletion rate was substantially smaller than in the case of the Ogallala Aquifer. Furthermore, only a few studies to date have evaluated the impact of policy makers' decisions on GWLs using either data-driven models (Feng et al., 2008) or semi-statistical water balance approaches (Butler et al., 2020a). A review of the literature reveals that ML has yet to be employed to assess the long-term impacts of management strategies on groundwater resources considering climate variability.

In the work reported here, we develop and evaluate a data-driven modeling architecture for long-term GWL forecasting in groundwater irrigated agricultural regions. The main components of the architecture are an ensemble learning model and a geostatistical interpolation technique: RF (random forests) and ordinary kriging, respectively. RF simulates annual GWL change in measurement points and these discrete GWL change forecasts are spatially distributed using kriging. The combination of ML and geostatistical methods has been applied in a number of studies simulating GWL spatiotemporally (Nourani et al., 2011; Tapoglou et al., 2014). However, we include aquifer saturated thickness (i.e., vertical distance from water table to bedrock) and the number of active high production wells, which have not been incorporated in previous studies,

enabling our model to capture decline in groundwater depletion rate as storage conditions evolve closer to complete depletion. Moreover, the input data equip the model with the capability to quantify the impacts of water conservation policies, namely well retirement plans, on future GWLs.

By employing the developed data-driven modeling framework in an intensively irrigated area overlying the Ogallala Aquifer, this study primarily aims to: (1) introduce a new input variable named groundwater withdrawal potential (*GWWP*), which is the product of aquifer saturated thickness and number of active high production wells, as a proxy for unavailable pumping data in long-term GWL projections; (2) evaluate the long-term impacts of climatological factors on groundwater availability and depletion time frames; and (3) assess the efficacy of well retirement policies in prolonging the lifetime of the aquifer under different climate conditions. While the proposed modeling framework is tested for the Ogallala Aquifer in Finney County in southwest Kansas, it can be applied to other stressed aquifers worldwide where groundwater pumping is a significant factor in GWL decline.

2.2. Materials and Methods

2.2.1. Study Area

Finney County in southwest Kansas is one of the most intensively irrigated areas across the High Plains Region owing to the great saturated thickness within the underlying Ogallala Aquifer (Figure 2.1). Groundwater development in the county began before the 1940s in Garden City and surrounding areas to the north of the Arkansas River. Over the next decades, as a result of advances in irrigation and drilling technologies, groundwater development rapidly expanded to the rest of the county and reached its peak in 1980 (Figure A1 in Appendix A). According to the

Water Information Management and Analysis System (WIMAS; Kansas Geological Survey, 2019c), 2534 irrigation wells were active in Finney County in 1980 and between 24% and 31% of the county's area has been irrigated since then.

There are some areas along the Arkansas River and mainly northwest of Garden City that historically were irrigated by diverting water from the river into unlined irrigation ditches (Figure 2.1 b, c). However, the river went dry in the region in the early 2000s, leading to the dependence of ditch service areas on groundwater as the main source of irrigation.

The Ogallala Aquifer in Finney County has been over-exploited over the past several decades, resulting in nearly 30 m decrease in average saturated thickness between 1952 and 2017. Unsustainable groundwater withdrawals, high dependence on the aquifer for irrigated agriculture, and the implementation of the Conservation Reserve Enhancement Program (CREP) have drawn researchers' attention to Finney County in recent years (Rouhi Rad et al., 2020b; Xiang et al., 2020). The reason for selecting Finney County as our study region, in addition to already mentioned reasons, is the abundance of annual GWL measurements from a network of 165 wells (Figure 2.1 c); the high variability of saturated thickness across the county area, providing the opportunity to train the model with data in a variety of depletion stages; and the availability of geologic data from well logs. Moreover, we do not expect a significant increase in the number of high production wells in the future due to the decreasing trend of active high production wells in the county since 1980 (Appendix A, Figure A1), making long-term GWL projections more reliable.

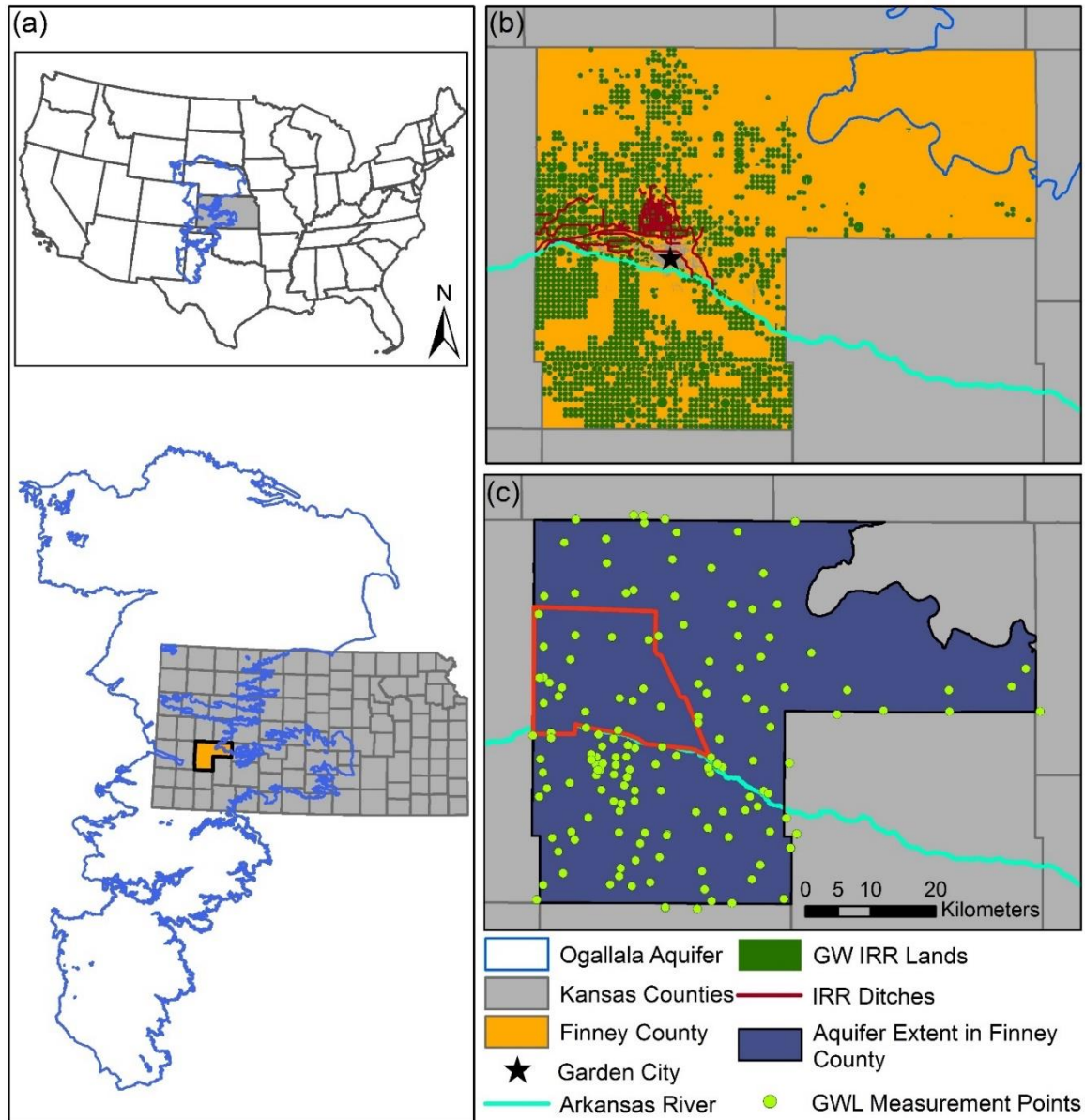


Figure 2.1. (a) Study area. (b) Groundwater irrigated lands (GW IRR Lands) and irrigation ditches (IRR Ditches). (c) Irrigation ditch companies' service area enclosed with red line and groundwater level (GWL) measurement points.

2.2.2. Random Forests Model Development

In this study, the RF technique is used to forecast GWL variations and subsequently GWL values (i.e., water table elevation values) in measurement points. The RF method is selected

because despite its relatively simple structure and ease of calibration, it is resistant to outliers, noise, and redundant data and can handle complex data of different statistical distributions with no need for data scaling (Breiman, 2001; Rodriguez-Galiano et al., 2014; Tyrallis et al., 2019). Moreover, as suggested by Galelli and Castelletti (2013), the RF method can be used directly for input ranking thanks to its intrinsic ability to quantify the relative importance of input variables. We have leveraged this capability of the RF technique to find the best subset of input variables without using any external algorithms. Moreover, the internal measurement of input variable importance makes the RF models more comprehensible compared to other black box ML models such as SVM (Rahman et al., 2020). Here we present steps taken toward RF model development and evaluation.

2.2.2.1. Random Forests

Random Forests (RF) is an ensemble learning algorithm introduced by Breiman (2001) for both classification and regression problems. The RF method employs an ensemble of Classification and Regression Trees (CARTs; Breiman et al., 1984) using bootstrapping and bagging methods (Breiman, 1996) to rectify the overfitting problem of individual trees attributed to their excessive flexibility (Biau and Scornet, 2016). Since GWL forecasting is a regression problem, the developed RF model in our study consists of an ensemble of single regression trees. In each regression tree, the bootstrapped sample of the original dataset is recursively partitioned at a series of internal (split) nodes. Each node is split into two subsets of data called child nodes by a split value. At each node, the algorithm searches through a random subset of input variables (features) to find the best split leading to minimum impurity in resultant child nodes.

To calculate impurity at each node, the algorithm fits a constant regression model to the data and computes regression error. The constant value is calculated as the mean of target variables

(labels) at each node and the common measure for regression error is mean square error (MSE). The best split at each node is found by maximizing the information gain (G) which is defined as the difference between parent node's impurity and the weighted sum of child nodes' impurity:

$$G(Q_m, \theta) = H(Q_m) - \left(\frac{N_l}{N_m} H(Q_l) + \frac{N_r}{N_m} H(Q_r) \right) \quad (2.1)$$

where Q represents dataset at each node, θ represents the candidate split, H is impurity function, N represents the size of dataset at each node, m denotes parent node, l denotes left child node, and r represents right child node. The impurity function (H) at node m is defined as:

$$H(Q_m) = \frac{1}{N_m} \sum_{y \in Q_m} (y - \bar{y}_m)^2 \quad (2.2)$$

where y denotes target variables and $\bar{y}_m$ is the mean of target variables at node m . The same process is repeated for each child node and each tree keeps growing until a stopping criterion is reached (Loh, 2011) at terminal (leaf) nodes. The output of RF is the arithmetic average (aggregation) of all trees' outputs. In this study, the Scikit-learn library (Pedregosa et al., 2011) of the Python programming language is used to construct the RF model.

2.2.2.2. Data Description and Input Variable Selection

Annual GWL measurements in Finney County spanning from 1980 to 2017 were obtained from the WIZARD Water Well Levels Database (Kansas Geological Survey, 2019a). In addition to all GWL measurement points in Finney County, we included a few points located within the immediate proximity of the county border to increase forecast accuracy in boundary areas (Figure 2.1c). Since the target variable is GWL variations, GWL measurements were converted to annual GWL changes for water years 1980 to 2016. We have considered water year (October through

September) instead of calendar year for our analysis as it starts with the aquifer recovery period (October through April) and ends with the irrigation period (May through September).

GWL data were filtered in a three-step process. First, GWL measurements during the irrigation period were ignored as they are prone to drawdown effects from pumping. Multiple measurements from a single well in the recovery period were averaged to provide one estimate per well for each water year. Second, GWL changes beyond 1.96 standard deviations from the mean (incorporating all GWL variation data) were considered as outliers and removed. Third, the investigation of available satellite-based data (Deines et al., 2019; Earth Resources Observation and Science (EROS) Center, 2019) reveals the majority of croplands in the study area were converted to center pivots by 1980 with the exception of the croplands located within the irrigation ditch companies' service area (marked by red polygon in Figure 2.1c). In this region, groundwater irrigated agriculture using center pivots has become prevalent since 2003. Therefore, all pre-2003 GWL variations in this region were excluded due to inconsistency in irrigation system as well as irrigation water source, emphasizing the importance of historical analysis in data-driven modeling efforts. After the three steps of filtering, 2,438 annual GWL change records from 165 wells were available for training and testing the RF model. The number of records in individual wells ranged from 2 to 37, with a median of 12.

Based on previous knowledge of the groundwater system in the study area, we initially incorporated a wide range of input variables into the RF model that could possibly affect GWLs on annual basis. Table 2.1 presents the list of initial input variables, their importance rank, time scale, category, and the source of basic data used to obtain/quantify them. Some of the input variables are among the most commonly used input variables in previous GWL forecasting studies (as indicated by Rajaei et al. (2019)), that is to say, groundwater depth (*GWD*), water year total

precipitation (P), average daily mean temperature in irrigation season (T), and water year mean river flow (F). The GWD is an indicator of groundwater depletion intensity; the P is a measure of soil moisture replenishment and groundwater recharge; the T represents soil moisture loss through evapotranspiration; and the F is a measure of aquifer recharge through the infiltration of a portion of stream flow (if there is any) into the river bed and banks. The rest of the variables have either never been considered or been considered in a few studies to date and will be briefly explained here.

Table 2.1. Overview of all input variables considered for groundwater level forecasting (GWL) using the random forests (RF) method

Importance Rank	Input Variable	Time Scale	Category	Source of Basic Data
1*	Groundwater withdrawal potential ($GWWP$)	Water year	Groundwater extraction intensity	WIMAS (Kansas Geological Survey, 2019c) and WIZARD (Kansas Geological Survey, 2019a)
2*	Mean SPEI-3** in irrigation period (SPEI-IRR)	Irrigation period	Climate	GRIDMET (Abatzoglou, 2013)
3*	Groundwater depth (GWD)	Water year	Groundwater hydrology	WIZARD (Kansas Geological Survey, 2019a)
4*	Total precipitation (P)	Water year	Climate	PRISM (PRISM Climate Group, 2019)
5*	Mean SPEI-3 in water year ($SPEI-WY$)	Water year	Climate	GRIDMET (Abatzoglou, 2013)
6*	Aquifer specific yield at groundwater level (Sy)	Water year	Geology	WWC5 (Kansas Geological Survey, 2019b)
7	Average daily mean temperature in irrigation period (T)	Irrigation period	Climate	PRISM (PRISM Climate Group, 2019)
8	Distance to closest active well (DCW)	Water year	Groundwater hydrology	WIMAS (Kansas Geological Survey, 2019c)
9	Mean river flow (F)	Water year	Surface water hydrology	Surface-Water Annual Statistics for the Nation (U.S. Geological Survey, 2019b)

* Final input variable

** SPEI-3 denotes the standardized precipitation evapotranspiration index with the aggregation time step of three months.

In agricultural regions, pumping significantly influences GWL variations and should be included as a model input. However, pumping data is seldom available in these regions. In lieu of

unavailable groundwater extraction data, previous studies have attempted to use other variables as a proxy for pumping, such as irrigation demand of major crops (Sahoo et al., 2017; Salem et al., 2018; Amaranto et al., 2019). In the current study, we introduce groundwater withdrawal potential (*GWWP*) as a new measure of pumping intensity that can be calculated at GWL measurement point *i* as follows:

$$GWWP = B_i \times W_i \quad (2.3)$$

where B_i is saturated thickness at location *i* and W_i is the number of active high production wells within a 3000 m radius of *i*. The radius value was selected through a search of values ranging from 50 to 3500 m. A given well is considered as high production if it is being used for irrigation, industrial, or municipal demands. The status of high production wells during the 1980-2016 period was obtained by analyzing water rights data. We evaluated the relevance of the *GWWP* compared to *B* and *W* by constructing an RF model with these three inputs and measuring their impurity-based importance (the term of impurity-based importance will be explained later in this section). The results show the superiority of the *GWWP* with the importance value of 0.49 over *B* and *W* with the importance value of 0.40 and 0.11, respectively. Since well capacity (defined as the maximum pumping rate that could be sustained throughout the irrigation season) is partly a function of aquifer saturated thickness (Harman, 1966), one may interpret the *GWWP* as an indicator of total maximum pumping rate in the vicinity of a given GWL measurement point. While the *GWWP* represents regional groundwater extraction intensity, distance to the closest active high production well (*DCW*) is included to capture the local impacts of pumping.

The standardized precipitation evapotranspiration index (SPEI; Vicente-Serrano et al., 2010) is a normalized drought index that fits aggregated differences between monthly precipitation

and potential evapotranspiration (PET) to a three-parameter log-logistic distribution to quantify departures from normal conditions, and has been used in the U.S. Great Plains region (Zambreski et al., 2018). We already have considered the T and the P as two climatic variables, but neither is able to solely represent soil moisture deficit which is a determinant of pumping intensity in each year. On the other hand, Afshar et al. (2022) have shown the SPEI has a high correlation with a soil moisture drought index, namely the standardized soil moisture index (SSMI), in the U.S. High Plains; therefore, the SPEI can be used as an indicator of soil moisture deficit in our study area. Moreover, the SPEI has been utilized as a surrogate for total annual pumping in a recent data-driven GWL modeling study in the southern High Plains of Texas and had the highest relative contribution among the model inputs (Ghaseminejad and Uddameri, 2020).

In the current study, gridded estimates of historical monthly accumulated precipitation and PET based on the Penman-Monteith methodology were retrieved from GRIDMET (Abatzoglou, 2013) for the 1980-2016 period. These variables were used to derive the SPEI with the aggregation time step of three months (SPEI-3) at each grid cell, since the SPEI-3 is more closely related to agricultural drought (Zambreski et al., 2018). We used the gridded SPEI-3 values to get water year mean (*SPEI-WY*) as well as irrigation period's mean (*SPEI-IRR*) of the SPEI-3 at GWL measurement points from 1980 to 2016. The *SPEI-IRR* is a measure of crop irrigation demand, whereas the *SPEI-WY* represents soil moisture depletion and replenishment mechanisms throughout a given water year.

The state of Kansas has a comprehensive database of well logs (Kansas Geological Survey, 2019b). Therefore, we examined the relevance of hydrogeological parameters in data-driven GWL models by incorporating aquifer specific yield at GWL (S_y) as a model input, since such category of data has been considered only in a few studies (Tsanis et al., 2008; Koch et al., 2019). To

estimate S_y , we compiled a well log dataset of 603 boreholes in Finney County and its vicinity (Appendix A, Figure A2a). Initially, the well logs were used to make the bedrock elevation raster which is required for the calculation of saturated thickness at GWL measurement points (Appendix A, Figure A2a). Additionally, we used the well logs along with historical water table elevation rasters to estimate S_y at each borehole from 1980 to 2016, by finding the lithology layers located within the $[GWL - 2.35, GWL + 1.08]$ interval and calculating the interval's weighted average specific yield based on the suggested values in Liu et al. (2010). The values of -2.35 and 1.08 correspond to the 2.5th and 97.5th percentiles of historical GWL changes distribution, respectively. The S_y values were then interpolated using ordinary kriging with an exponential semivariogram model to generate gridded estimates of S_y (Appendix A, Figure A2b; see section 2.3 for more details on kriging). The resultant grids were used to estimate S_y at GWL measurement points. S_y calculations were performed using the Python ArcPy package.

While the RF method is susceptible to low-dimensional rather than high-dimensional input data (Wang et al., 2018), it is appropriate to reduce high dimensionality by finding the most relevant input variables. We have used the RF algorithm to rank the input variables, and consequently have selected the best subset of them. In the RF algorithm, the total information gain (G , see Eq. (1)) attained by each input variable in a given tree is normalized by total G at all nodes of the tree, resulting in a feature's relative importance in a single tree. The relative importance of each feature in the RF model is obtained by averaging a feature's relative importance in all individual trees. This measure of feature importance is called the impurity-based importance.

We have selected the best subset of input variables through an iterative process. In this process, an RF model with 500 trees was constructed and trained using historical data from 1980 to 2011 at each iteration and the feature with the least impurity-based importance was omitted

from the succeeding iteration. Since our single goal during the input variable selection process was to quantify the relative importance of model inputs, the RF models were parameterized in such a way that all available input variables at a given iteration were explored to find the best split at each node, rather than searching through a random subset of them. The procedure was repeated until all remaining input variables attained an impurity-based importance value of greater than or equal to 0.1, which was met in the fourth iteration (Figure A3 in Appendix A). The final input variables are *GWWP*, *SPEI-IRR*, *GWD*, *P*, *SPEI-WY*, and *Sy* (Table 2.1).

We selected an annual time step for the RF model, with the assumption that input variables influence GWL change within the same time step, thereby removing the need to perform the time lag analysis of input variables, as has been performed in previous studies (e.g., Amaranto et al., 2019). The GWL forecasting scheme of the RF model in this study is the one-step-ahead forecasting approach, i.e., the model utilizes input data in year t to forecast GWL change in year t and subsequently GWL value in year $t+1$.

2.2.2.3. Random Forests Model Training, Testing, and Evaluation

The common procedure in constructing data-driven GWL models is that a separate model is built and calibrated for each GWL measurement point with a long record of historical data (Sahoo et al., 2017; Amaranto et al., 2019). While this procedure yields high levels of accuracy at measurement points, it ignores a considerable portion of measured data at wells with a rather short record of GWL measurements. The procedure also leads to noticeable interpolation errors in creating gridded GWL data due to the scarcity of long-record wells. Moreover, the RF model needs to be trained with a wide range of *GWWP* values in order to capture decline in groundwater depletion rate as the system evolves closer to complete depletion. Therefore, in this study,

historical model inputs and outputs at all GWL measurement points are lumped together and a single RF model is developed for all the points.

The historical data were split into the two temporal periods of training (1980 to 2011) and testing (2012 to 2016). The training dataset was used to construct and calibrate the RF model. The k -fold cross-validation technique ($k = 10$) was adopted to calibrate the model hyperparameters, and bias and root mean square error (RMSE) were used as model performance metrics in cross-validation. The hyperparameters chosen for calibration were the number of trees, the number of input variables considered at each split, the minimum number of samples required to split an internal node, and the minimum number of samples required to be at a terminal node with the final values of 600, 2, 4, and 2, respectively.

After training and calibration, the RF model performance is independently examined by running the model for the testing period and comparing its outputs with measured data via four different model performance metrics, namely bias, root mean square error (RMSE), the Pearson correlation coefficient (R), and the Kling-Gupta Efficiency (KGE; Gupta et al., 2009). In model testing, we only consider GWL measurement points with available records over the entire testing period, that is to say 52 points in total. The performance metrics are calculated based on the two categories of residuals (defined as the modeled GWL subtracted from the measured GWL), namely discrete and cumulative residuals. The metrics calculated based on discrete residuals measure model performance in one-year-ahead GWL forecasting; i.e., model performance in each year is independent of its performance in previous years. On the other hand, the metrics computed based on cumulative residuals demonstrate the long-term forecast capabilities of the model, since errors in a given year will propagate into the next years.

The performance metrics were computed for the RF model as well as a set of simpler data-driven models, that is to say, multiple linear regression (MLR), multiple 2nd order non-linear regression (MNLR-2nd), and multiple 3rd order non-linear regression (MNLR-3rd). In addition to these simpler techniques, we developed and calibrated an SVM model, which is a robust and commonly used ML method in GWL modeling, and compared its performance with the RF model. All these additional modeling techniques were used as reference points for the evaluation of the RF model's forecast skill in the testing period.

To develop the SVM model, the input variables were scaled to have unit variance and zero mean except for *SPEI-IRR* and *SPEI-WY* which are scaled intrinsically. Similar to recent GWL forecasting studies (Amaranto et al., 2018; Rahman et al., 2020), radial basis function kernel is selected for the SVM model. The SVM model was calibrated using the grid search cross-validation technique and by finding the values of three hyperparameters, namely cost, epsilon, and gamma. We employed the Scikit-learn library (Pedregosa et al., 2011) of the Python programming language to develop and calibrate the SVM model. The details of the SVM method are presented in Vapnik (1999).

To further evaluate the RF model performance, we compared annual reported total groundwater use in the county (Kansas Geological Survey, 2019c) with model-estimated annual decrease in total groundwater storage. The RF model outputs along with the ordinary kriging technique can be used to generate gridded saturated thickness values as well as gridded weighted average specific yield values of all lithology layers located below GWL. These two grids then can be used to estimate total groundwater storage (V) in the study area as follows:

$$V = \sum_{c=1}^{c=N} B_c \times Sy_c \times \Delta x \times \Delta y \quad (2.4)$$

where B_c is saturated thickness in cell c , Sy_c represents weighted average specific yield in cell c , N denotes the total number of cells, Δx is cell size in x direction, and Δy is cell size in y direction.

2.2.2.4. Relative Importance of Input Variables

We quantified the relative importance of input variables via the two approaches of impurity-based (see Section 2.2.2.2) and permutation-based feature importance to understand underlying non-linear interactions between model inputs and outputs. The impurity-based importance values were derived from the calibrated RF model where a random subset of features with a size of two was considered at each tree node to find the best split.

The permutation-based feature importance is defined as decrease in a model's skill score caused by random permutation of a given input variable (or a group of variables) for a number of times, while the rest of the input variables are left intact. Therefore, the more important a feature the greater decrease in model's skill score. To compute the permutation-based importance values, we randomly permuted each input variable 50 times and computed the average relative increase in the mean square error (MSE) value of the training dataset using the k -fold cross-validation technique ($k = 10$). We also collectively permuted the climatic variables, namely P , $SPEI-IRR$, and $SPEI-WY$, to estimate their joint importance. Incorporating the k -fold technique enables us to quantify the influence of input variables on GWL forecasts made using unseen data during the model training.

2.2.3. Long-term Groundwater Level Projections

After RF model development and evaluation, the model was trained for the last time using all historical data from 1980 to 2016. Then, the finalized RF model was employed in combination with ordinary kriging to forecast future annual GWL changes from 2017 to 2099 under various climate and management scenarios. Kriging is applied as a “best linear unbiased estimator” to create smooth and continuous rasters (Isaaks and Srivastava, 1989). We select ordinary kriging, since it is a well-known geostatistical interpolation technique and has been employed along with ML models for GWL projection in previous studies (Nourani et al., 2011; Tapoglou et al., 2014; Chang et al., 2016). The Geostatistical Wizard tool in ArcMap was used to determine kriging parameters, namely semivariogram model type, lag size, major range, partial sill, nugget, and search radius features. These parameters were estimated based on kriging’s RMSE computed using the leave-one-out cross validation technique.

2.2.3.1. Modeling Framework for Long-term Groundwater Level Projections

The modeling framework developed for spatiotemporal GWL forecasting in the long term is shown in Figure 2.2. The calibrated and trained RF model is the backbone of this modeling framework. The input variables of the RF model can be broadly classified into two groups according to their update mechanism. The first group includes climatic variables derived from downscaled climate projections, namely P , $SPEI-IRR$, and $SPEI-WY$. These variables are estimated ahead of long-term simulations and will not be affected by model outputs. The second group consists of input variables that are a function of GWL and vary with changes in GWL, namely S_y , $GWWP$, and GWD . Unlike the first group, the second group of variables is updated dynamically during the entire simulation period as a result of annual GWL variations.

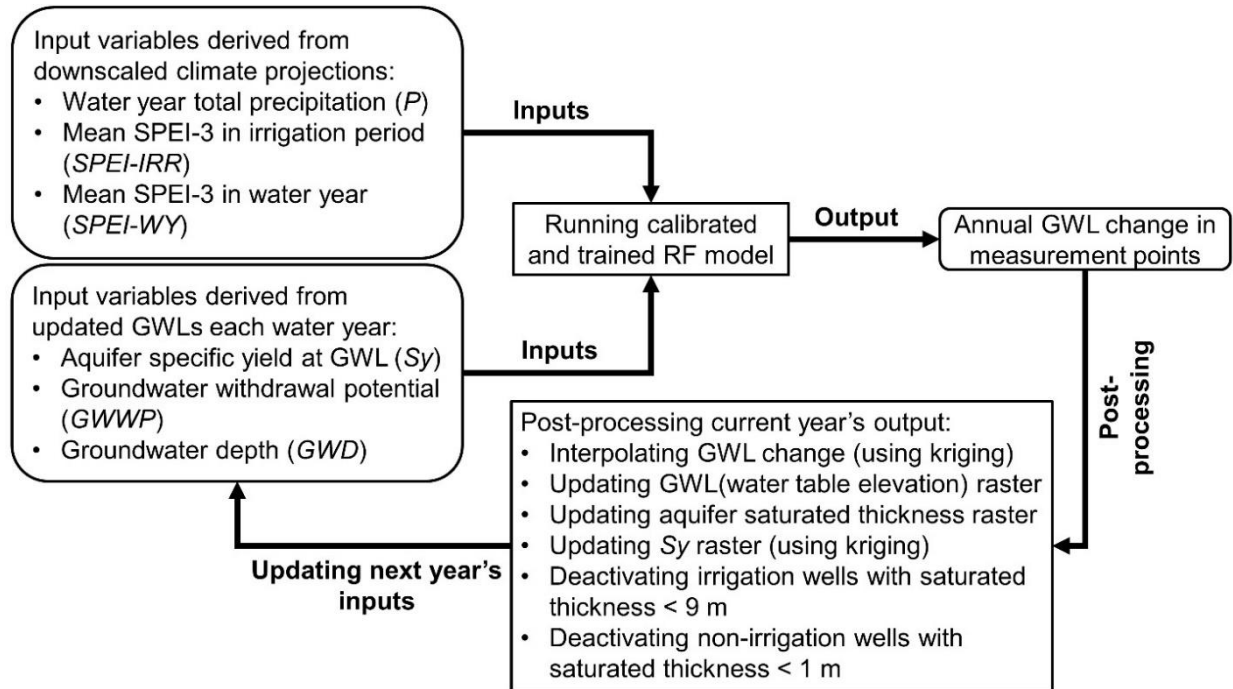


Figure 2.2. Modeling framework.

The RF model uses the input variables to forecast annual GWL change at measurement points. The RF model outputs are then post-processed through a series of steps, yielding a number of secondary outputs. In the first step of post-processing, the GWL changes in measurement points are interpolated using ordinary kriging with a Gaussian semivariogram model. In the next step, the GWL raster is updated for the next water year by adding the GWL change raster to the current year's GWL raster. The saturated thickness raster is then updated by subtracting the bedrock elevation raster from the updated GWL raster. The updated GWL raster is also used to update S_y values at borehole locations, which are then interpolated to update the S_y raster for the next water year using ordinary kriging with an exponential semivariogram model (see section 2.2.2.2 for more details on computing S_y value at boreholes).

Updating the status of high production wells is the last step in the post-processing of the RF model outputs. In this study, two deactivation criteria are considered for high production wells: a non-irrigation well becomes inactive when saturated thickness drops below 1 m (i.e., well goes dry), whereas an irrigation well becomes inactive if saturated thickness drops below 9 m [i.e., well ceases to support irrigated crop production due to low well capacity (Schloss et al., 2000; Rawling and Rinehart, 2019)]. The RF model outputs together with the secondary outputs are used to update the GWL dependent input variables for the next water year. The whole modeling workflow is carried out through a set of Python programming language scripts developed for the current study, incorporating the Scikit-learn library (Pedregosa et al., 2011) and the ArcPy package.

2.2.3.2. Climate Projections

Statistically downscaled gridded monthly precipitation and PET from 20 global climate models (GCMs) of the Coupled Model Intercomparison Project Phase 5 (CMIP5) were used to derive future projections of P , $SPEI-IRR$, and $SPEI-WY$ with the spatial resolution of ~ 4 km (Abatzoglou and Brown, 2012; Taylor et al., 2012). The grid cell values were then extracted at GWL measurement points to be used as the RF model inputs. The downscaling technique employed was the Multivariate Adapted Constructed Analogs (MACA) procedure, which has the advantages of computational efficiency, higher accuracy than simple interpolation approaches, and preservation of the first principles of meteorology through joint downscaling measures (Abatzoglou and Brown, 2012; Zhang et al., 2022). Daily maximum and minimum temperature, wind velocity, precipitation, and solar radiation were downscaled during this process.

For the baseline period, historical observations from GRIDMET (Abatzoglou, 2013) were used for downscaling the projection data. The MACA first applies the bias correction technique of quantile mapping to adjust the mean and variance of the GCM daily data to GRIDMET using the

projected and historical runs, followed by an epoch adjustment to remove the potential of finding no analog in the historical period. Next, the best analog is identified using thirty predictor patterns centered around a 45-day window on each calendar date. This analog procedure is conducted jointly for temperature and dew point to improve coherence between downscaled fields, whereas wind velocity and precipitation are downscaled individually. Epoch adjustments are reintroduced, and quantile mapping is performed again to ensure statistical moments are consistent with observations. The daily value(s) obtained after quantile mapping is the final downscaled daily variable. Parameter estimates for the log-logistic distribution in the SPEI calculations were calibrated using the downscaled data from 1980 to 2016 and applied similarly for the projection period from 2017 to 2099 at each grid cell. Because of uncertainties in future trajectory of greenhouse gas (GHG) emissions, GCM projections for two different representative concentration pathways (RCP) scenarios, namely RCP 4.5 and RCP 8.5, are included in this study. See Table A1 in Appendix A for a list of all GCMs considered in the current study along with their resolution and corresponding institution.

2.2.3.3. Long-term Groundwater Level Projections under Different Climate and Management Scenarios

The developed modeling framework together with the downscaled climate projections are leveraged to evaluate the long-term impacts of climate variability and changes on future GWLs and groundwater availability in the study area. The modeling framework is executed for 40 different climate scenarios from 2017 to 2099, i.e., 20 GCMs and 2 RCPs.

In addition to running the model for climate scenarios under status quo management condition, five different hypothetical well retirement plans are defined and reflected in *GWWP* values, namely 10%, 20%, 30%, 40%, and 50% retirement plans. The 10% retirement plan

involves the random selection of 10% of active irrigation wells at the beginning of the projection period and their uniform deactivation over a 10-year period (i.e., 2021-2030). This plan is converted into the other plans through augmenting the initial 10% well retirement by 10% increments during the same deactivation period. To assess the integrated effects of climatological and regulatory factors, we run the model for a combination of six management and two climate scenarios (i.e., a total of 12 scenarios) from 2017 to 2099. The five hypothetical retirement plans plus one no-action plan (i.e., baseline) constitute the management scenarios. The well retirement plans are hypothetical which means neither their political acceptability nor economic consequence is studied here. Since we want to evaluate well retirement plans under two different climate conditions, the climate scenarios are derived from the average of GCMs projections for RCP 4.5 and for RCP 8.5.

2.3. Results and Discussion

2.3.1. Random Forests Model Testing and Evaluation

2.3.1.1. Random Forests Model Performance in Testing Period

Figure 2.3a presents the performance metrics of the RF model along with the SVM model and other three simpler models. In this figure, all the metrics that correspond to discrete residuals are obtained through averaging the metrics of individual GWL measurement points; the bias and the RMSE values that correspond to cumulative residuals are computed based on cumulative residual values in 2016 in all the measurement points; these residuals in fact compare the position of modeled GWLs versus measured values at the end of the testing period.

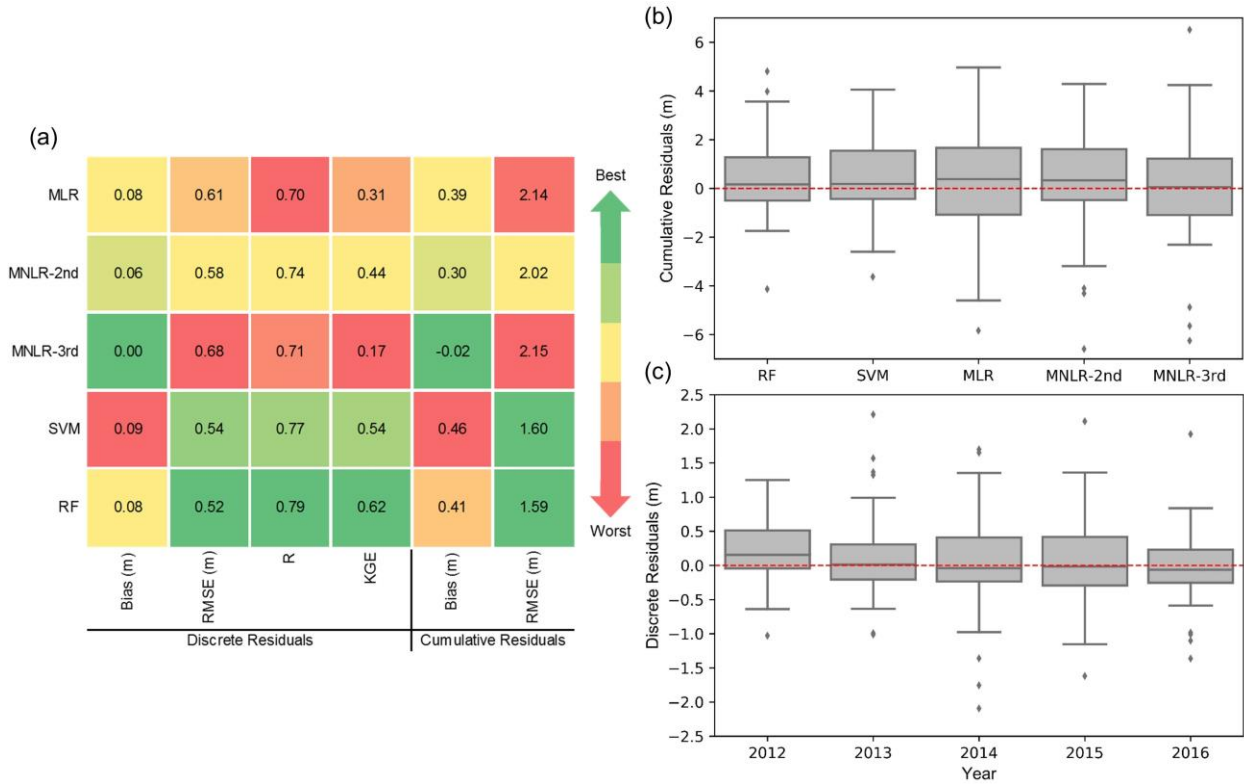


Figure 2.3. (a) Comparison of performance metrics for the RF model along with four other models in the testing period. (b) Box plots of cumulative residuals at the end of the testing period in different models. (c) Box plots of the RF model's discrete residuals in the testing period.

The comparison of the RF model with the SVM model shows that the RF model outperforms the SVM model with respect to all metrics (Figure 2.3a). Additionally, the RF model consistently has the best performance based on all metrics except for the bias compared to the three simpler models. The positive value of bias indicates either underestimation of GWL decline or overestimation of GWL rise, and conversely negative value of bias indicates either overestimation of GWL decline or underestimation of GWL rise. Considering the characteristics of the study area, bias values reveal that all models tend to underestimate GWL decline in the testing period except for the MNLR-3rd model.

The distribution of cumulative residuals at the end of the testing period (Figure 2.3b) reveals that the extraordinary low bias value of the MNLR-3rd model is attributable to large negative residuals in a few GWL measurement points. In the RF model, 87% of GWL measurement points have a cumulative residual within the range of ± 1.75 m with the mean value (i.e., bias) of 0.10 m, whereas in the MNLR-3rd model, 73% of cumulative residuals fall within the same range with the mean value of 0.13 m. This comparison shows the balanced performance of the RF model in the vast majority of the measurement points.

The better performance of the RF model compared to the SVM model, which is a robust ML technique in GWL modeling, as well as the simpler methods provides further justification for the selection of the RF technique in this study. The cumulative residuals of the RF model at the end of the testing period with RMSE = 1.59 m is comparable with the values attained by Sahoo et al. (2017) in the Ogallala Aquifer for the testing period of 2003 to 2012, where a majority of cumulative residuals in the last year fell within ± 2 m. It should be noted that in the referenced study a separate highly-parametrized ML model with pre-processed input data (i.e., a hybrid ANN model) was developed and calibrated for each individual monitoring well, resulting in slightly better performance of their models in comparison with our RF model.

To investigate the performance of the RF model in each testing year, a time series of discrete residuals distributions is depicted in Figure 2.3c. Acknowledging a slight general tendency for the underestimation of GWL declines, the distributions of residuals suggest fairly unbiased GWL forecasts in all the years except 2012 which is the second driest year (after 2011) in terms of *SPEI-IRR* and *SPEI-WY* during the 1980-2016 period. The extreme dry condition in 2011 and 2012 corresponds to the Southern U.S. drought that affected large parts of the country in the 2010-2012 period. Biased GWL forecasts in 2012 can be attributed to this drought; in fact, the prolonged

extreme dry condition led to soil moisture depletion, forcing the farmers to heavily rely on groundwater for crop production in this year. Since the RF model has not been trained with such an unprecedented dry condition, it underestimates GWL declines in the majority of cases in 2012. The reduced accuracy of data-driven GWL models under climate extremes is not unique to this study (Ghaseminejad and Uddameri, 2020; Nourani et al., 2022b).

In addition to the temporal evaluation, a spatial analysis of the RF model's performance metrics, calculated based on cumulative residuals, provides a better picture of the model's capabilities for long-term GWL projections and also reveals possible spatial anomalies in model performance (Figure 2.4). The value of bias is within ± 0.50 m in 52% of the points, is greater than 0.50 m in 33% of the points, and is less than -0.50 m in 15% of the points. This implies the RF model generally underestimates GWL declines during the testing period. It can be seen that 60% of the points have a RMSE value of less than 0.75 m, while only 10% of the points have a RMSE value of greater than 2 m. The R value is greater than 0.9 and 0.5 in 63% and 79% of the points, respectively. In 42% of the points, the KGE is greater than 0.7, while it is greater than 0.5 in 63% of the points. The KGE may not seem satisfactory in 37% of the points with values less than 0.5; however, the value of KGE is greater than -0.41 in 88% of the points, suggesting that the model's overall performance is significantly better than the mean values (Knoben et al., 2019) in the vast majority of points. The comparison of these results with the performance metrics of an integrated space-time ANN (IST-ANN) model (Ghaseminejad and Uddameri, 2020) implies the adequate performance of the RF model, taking into account the simplicity of development and calibration.

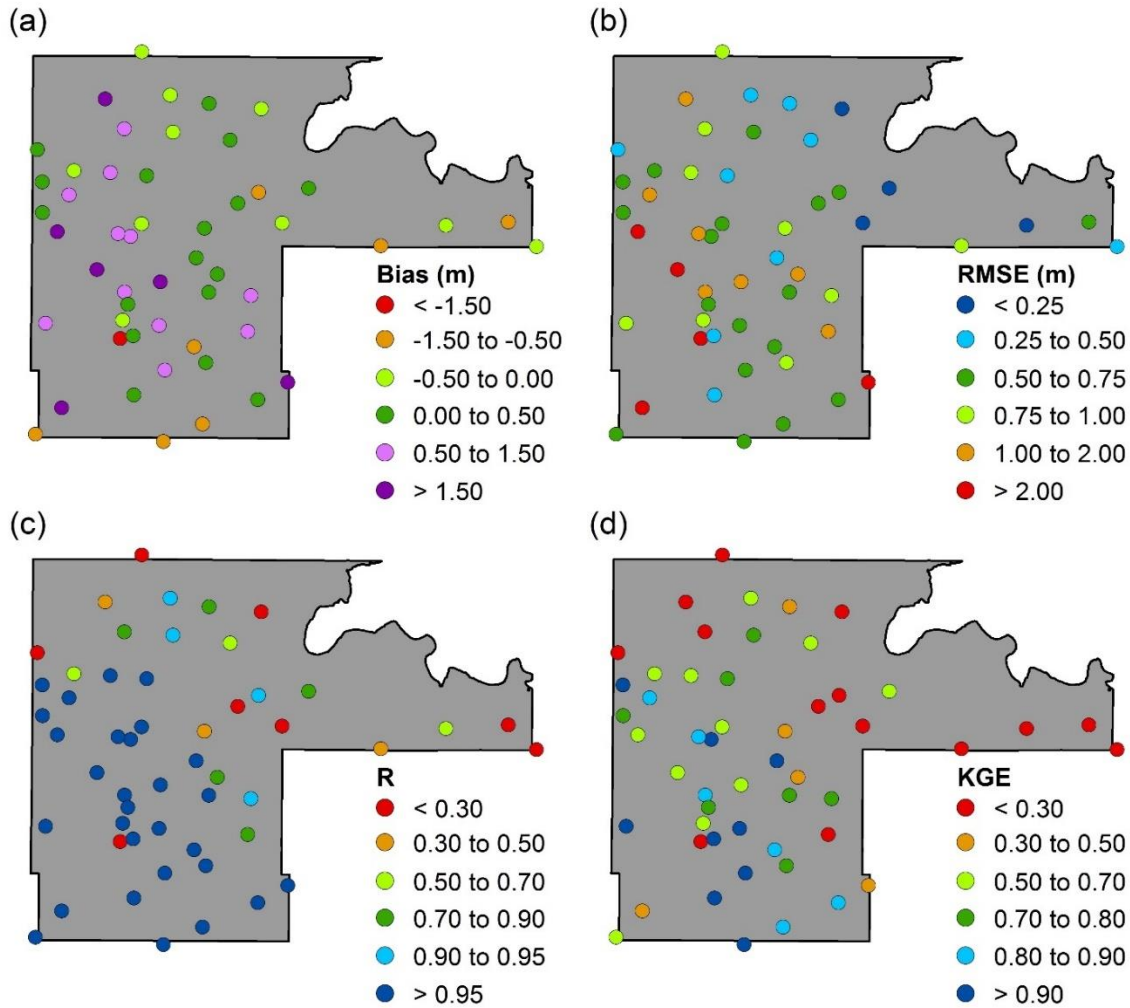


Figure 2.4. Performance metrics of the RF model in groundwater level measurement points.

There is no spatial trend in the values of bias and RMSE (Figure 2.4). However, a spatial pattern can be detected in the R and the KGE with clustered regions of low metric values. The regions located along the aquifer boundary on the northeast of the county as well as the regions in the northwest of the county are overlying portions of the aquifer with small saturated thickness (less than 20 m). Due to small well capacity values in these regions, groundwater extraction for irrigation is not as intensive as the rest of the county, leading to noisy GWL fluctuations. Because of such noisy behavior, the difference between measured and modeled variance increases, leading

to decreased values of R and KGE in these regions; on the other hand, the bias and the RMSE metrics indicate good overall performance in these regions, suggesting these two metrics could be misleading in regions characterized by small range of GWLs (Nourani et al., 2022b). The diminished performance of ML models due to noisy GWL fluctuations has been reported in previous studies for shallow wells (Rakhshandehroo et al., 2018) and regions with shallower GWLs and less pumping intensities (Sharafati et al., 2020).

To look at the RF model performance from a totally different perspective, the annual decrease in total groundwater storage forecasted by the model (see Eq. 4) is compared with annual groundwater use in Finney County from 2012 to 2016 (Figure 2.5). Due to the absolute dominance of the groundwater sink term (i.e., groundwater withdrawal) in the study area, the groundwater storage variations and annual groundwater use data are appropriately correlated with $R = 0.9858$.

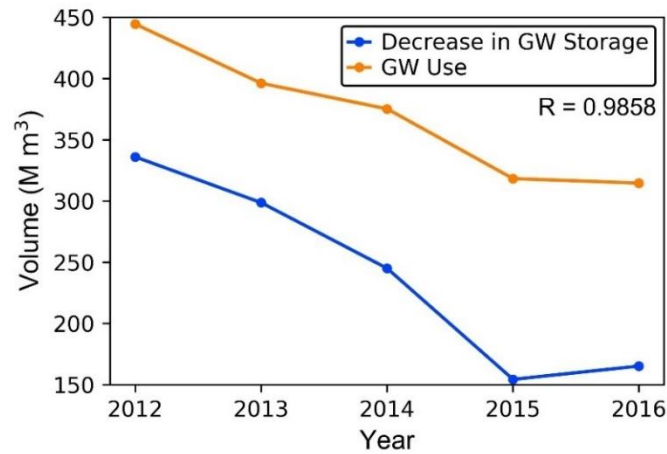


Figure 2.5. Comparison of annual decreases in total groundwater (GW) storage projected by the RF model with annual GW use data (Kansas Geological Survey, 2019c). R denotes the correlation coefficient of these two time series.

2.3.1.2. Random Forests Model Sensitivity Analysis

The sensitivity analysis of the RF model is carried out through the quantification of input variables' contribution using the two approaches of impurity-based (Figure 2.6a) and permutation-based (Figure 2.6b) feature importance (see Section 2.2.2.4). All input variables have the same ranking in both approaches; *GWWP* is the most important variable, followed by *GWD*, *SPEI-IRR*, *P*, *SPEI-WY*, and *Sy*. Earning the highest ranking of model inputs by the *GWWP*, underscores the combined impact of two neglected variables in previous studies, namely saturated thickness and the number of active high production wells, on GWL variations in an intensively irrigated region. We note that saturated thickness and depth to groundwater table, the former corresponding to *GWWP* and the latter representing *GWD*, are among the most influential irrigation drivers in western Kansas (Lamb et al., 2021). Both *GWWP* and *GWD* are indicators of groundwater development intensity (i.e., degree of pumping establishment) across the study area, offering a process-based justification for their top ranking.

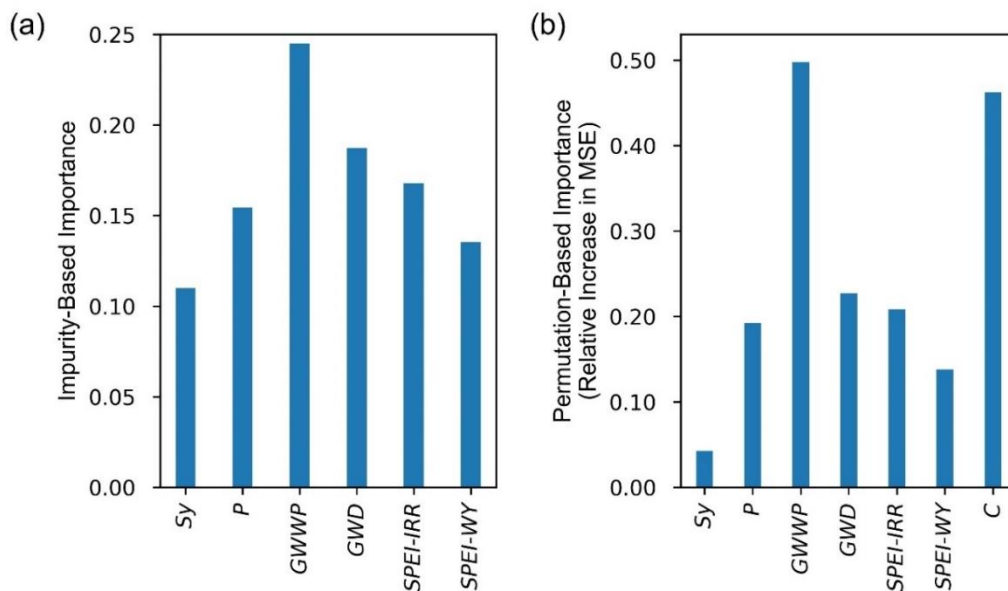


Figure 2.6. Importance of input variables in the RF model. (a) Impurity-based relative importance values. (b) Permutation-based importance values.

The climatic variables in the current study (i.e., *SPEI-IRR*, *P*, and *SPEI-WY*) are believed to only have indirect impacts on GWLs, due to deep GWLs and intensively irrigated agriculture. In aquifers with deep GWLs, the direct impacts of climatological factors on GWLs through influencing groundwater recharge rates can be dominated by their indirect impacts affecting irrigation demands (Russo and Lall, 2017). The higher importance of *SPEI-IRR* than *SPEI-WY* also implies the indirect impacts of climatic variables as the *SPEI-IRR* likely affect irrigation water demand more substantially. The joint permutation-based importance of climatic variables (*C* in Figure 2.6b) reveals the collective role of these variables in the RF model; however, the *C* is still dominated by the *GWWP*. The *Sy* has the least importance value among the input variables which is likely due to the absolute dominance of groundwater extraction over GWL variations in the study area, as represented directly and indirectly by the rest of the inputs. Another possible reason could be inaccurate *Sy* estimates, arising from interpolation errors and/or approximate representation of lithology layers in well log data (Butler et al., 2020b). Tsanis et al. (2008) also incorporated *Sy* as an additional feature in their ANN model and noticed slight improvement in their model performance.

The impurity-based feature importance approach is prone to overfitting, i.e., it tends to overestimate the importance of features that do not actually contribute to model outputs but are being utilized for overfitting during model training. On the other hand, the permutation-based importance values are computed using unseen data during the training. Thus, the constancy of input variables' ranking implies that none of the input variables cause overfitting during the RF model training.

2.3.2. Long-term Projections

2.3.2.1. Climatic Variables Projections

The spatially averaged historical (from 1980 to 2016) and projected (from 2017 to 2099) values of the RF model's climatic input variables are presented in Figure 2.7. The comparison of projected variables with historical records shows the percentage of projected data that exceed the historical range is 15%, 14%, and 9% for *P*, *SPEI-IRR*, and *SPEI-WY* in RCP 4.5, respectively, and is 14%, 16%, and 20% for *P*, *SPEI-IRR*, and *SPEI-WY* in RCP 8.5, respectively. Therefore, it can be inferred that the RF model is not extrapolating GWL variations, with respect to climatic inputs, in most cases of future climate scenarios. A decreasing temporal trend is noticeable in the projected values of *SPEI-IRR* and *SPEI-WY* for RCP 8.5, implying the negative impacts of GHG emissions on drought conditions in the study area. The SPEI ranges within ± 3 , with negative values indicating drier than normal climatic conditions and positive values indicating wetter than normal conditions.

We use the ensemble mean of GCMs projections to assess the impact of two different climate conditions on well retirement policies. The ensemble mean of GCMs projections for RCP 4.5 constitutes the “RCP 4.5 ensemble mean” climate scenario with the average value of 489 mm, -0.42, and -0.71 for *P*, *SPEI-IRR*, and *SPEI-WY* during the projection period, respectively; the ensemble mean of GCMs for RCP 8.5 forms the “RCP 8.5 ensemble mean” climate scenario with the average value of 474 mm, -0.75, and -0.96 for *P*, *SPEI-IRR*, and *SPEI-WY*, respectively.

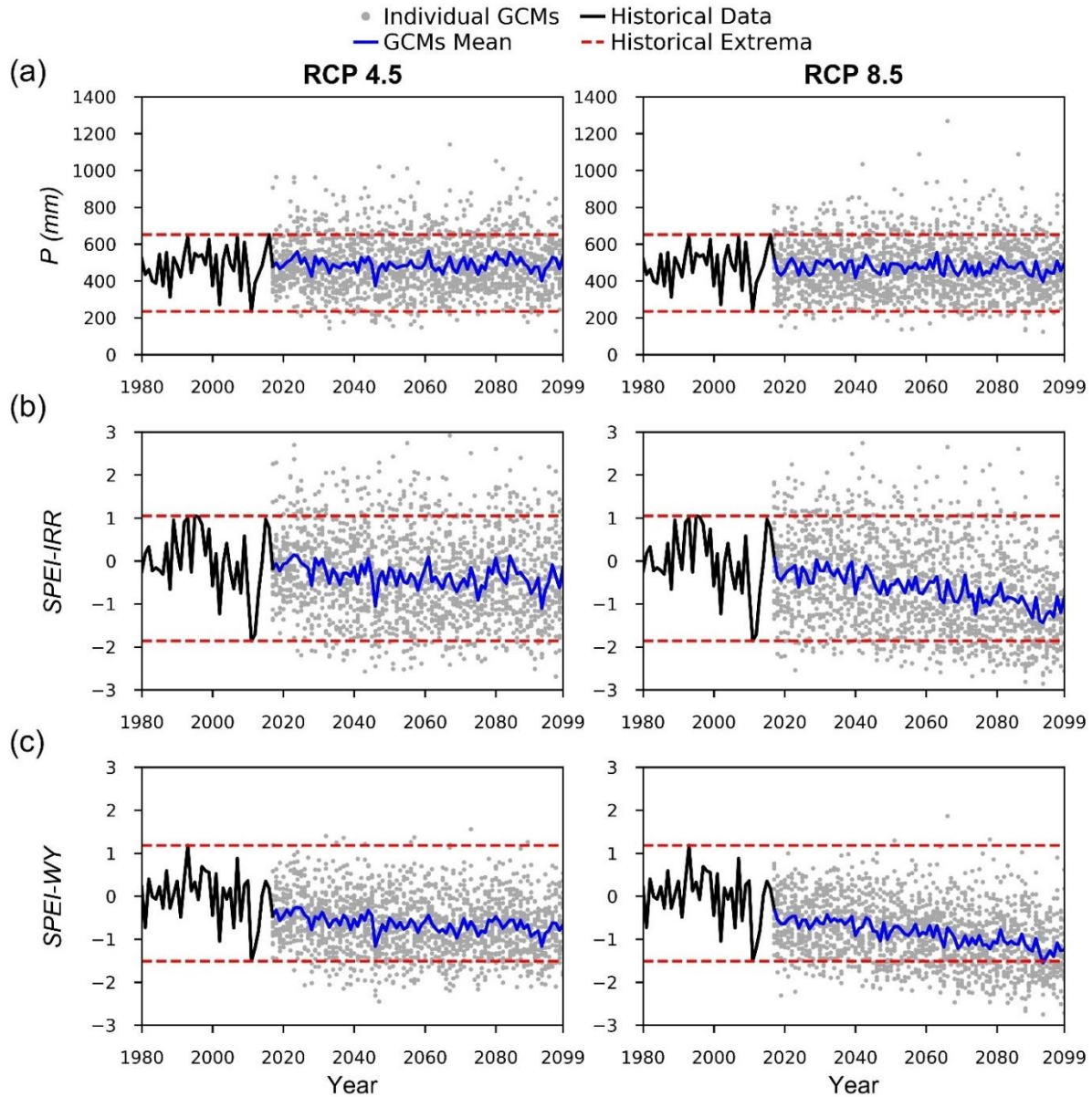


Figure 2.7. Spatially averaged historical and projected values of the climatic input variables in Finney County.

2.3.2.2. Long-term Groundwater Level Projections under Various Climate Conditions

To better analyze the RF model's long-term forecasts at individual GWL measurement points under different climate scenarios, we select six measurement points and plot saturated

thickness variations at each point (Figure 2.8). These simulations are done under “business as usual” condition with no shifts in irrigation technology, crop choices, cultivars, and/or water use regulations. The selected GWL measurement points represent a wide range of saturated thickness values at the beginning of the projection period. The reason for presenting the forecasted values in the form of saturated thickness rather than GWL is that saturated thickness provides a more complete assessment of groundwater availability. The ensemble means of saturated thickness forecasts for RCP 4.5 and for RCP 8.5 present the overall trend of groundwater depletion in each emission scenario at the selected GWL measurement points (Figure 2.8b). Saturated thickness forecasts at all the points, except point 6, clearly show a decreasing trend in depletion rate as the system progresses towards aquifer depletion, representing the S-shaped logistic curve as suggested by Steward et al. (2013). The RF model’s capability to capture this decreasing trend is obtained through introducing the *GWWP* as an input variable, deactivating wells as a result of groundwater depletion, and training the model with all historical data across the study area corresponding to different depletion stages.

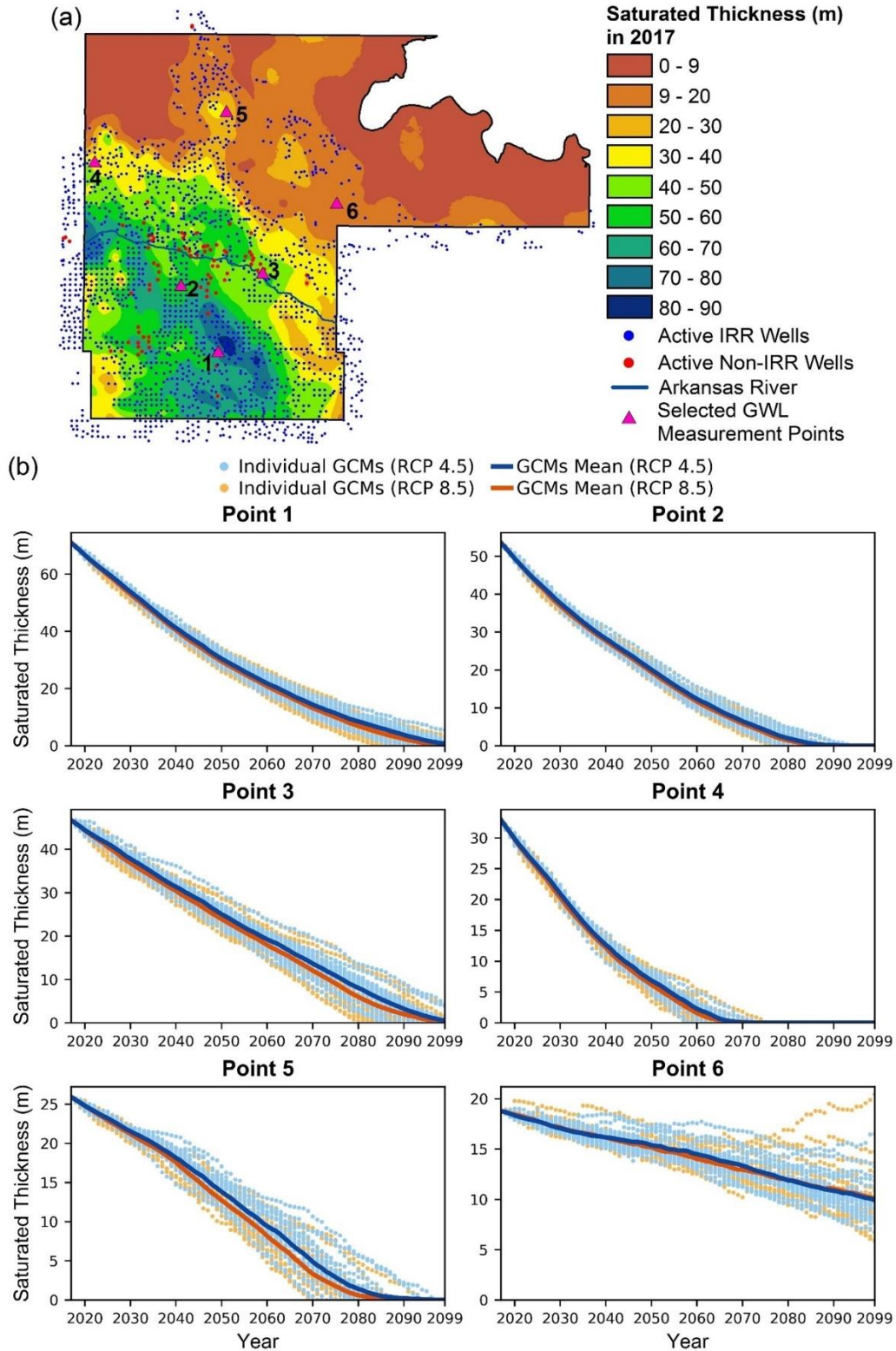


Figure 2.8. (a) Selected groundwater level (GWL) measurement points, aquifer saturated thickness, and active irrigation (IRR) and non-irrigation (Non-IRR) wells in 2017. (b) Saturated thickness projections at the selected GWL measurement points from 2017 to 2099.

The different depletion mechanism at point 6 can be attributed to noisy GWL fluctuations as a result of insignificant groundwater withdrawals in regions with small saturated thickness and low well density. These regions have witnessed a rise in GWLs in 2011 which has been the driest year since 1980, with respect to all three climatic variables, in the study area. We ascribe this phenomenon to producers' decision to switch from irrigated to either dryland (rain-fed) or no crop production during abnormally dry conditions in regions where pumping is not heavily established due to low well capacity values. Such decisions are manifested in a sudden increase in saturated thickness at point 6 in years after 2070 under one specific climate scenario, namely the IPSL-CM5A-MR GCM model for RCP 8.5, being characterized by extreme dry conditions in years succeeding 2070. These results show the RF model holds promise for capturing spatiotemporal heterogeneities in producers' irrigation decisions based on historical data, although there is no guarantee that the producers make the same decisions in future. On the other hand, a physically based groundwater model cannot simulate such heterogeneities unless coupled with an agent-based agro-economic model (e.g., MOD\$\$AT; Rouhi Rad et al., 2020b).

To compare groundwater availability under different climate scenarios in a spatially lumped manner, we calculate total groundwater storage in the study area (see Eq. 4) from 2017 to 2099 for each climate scenario (Figure 2.9). The results indicate the total volume of water in storage decreases by more than 87% by the end of the century in all climate scenarios; however, each scenario affects groundwater depletion differently (Figure 2.9a). For example, in the climate scenario correspondent to the IPSL-CM5A-MR GCM model for RCP 8.5, despite rapid depletion in the first half of the projection period, groundwater storage starts increasing in years after 2070 due to the cessation of irrigated agriculture during severe drought events in regions with small saturated thickness and low well density.

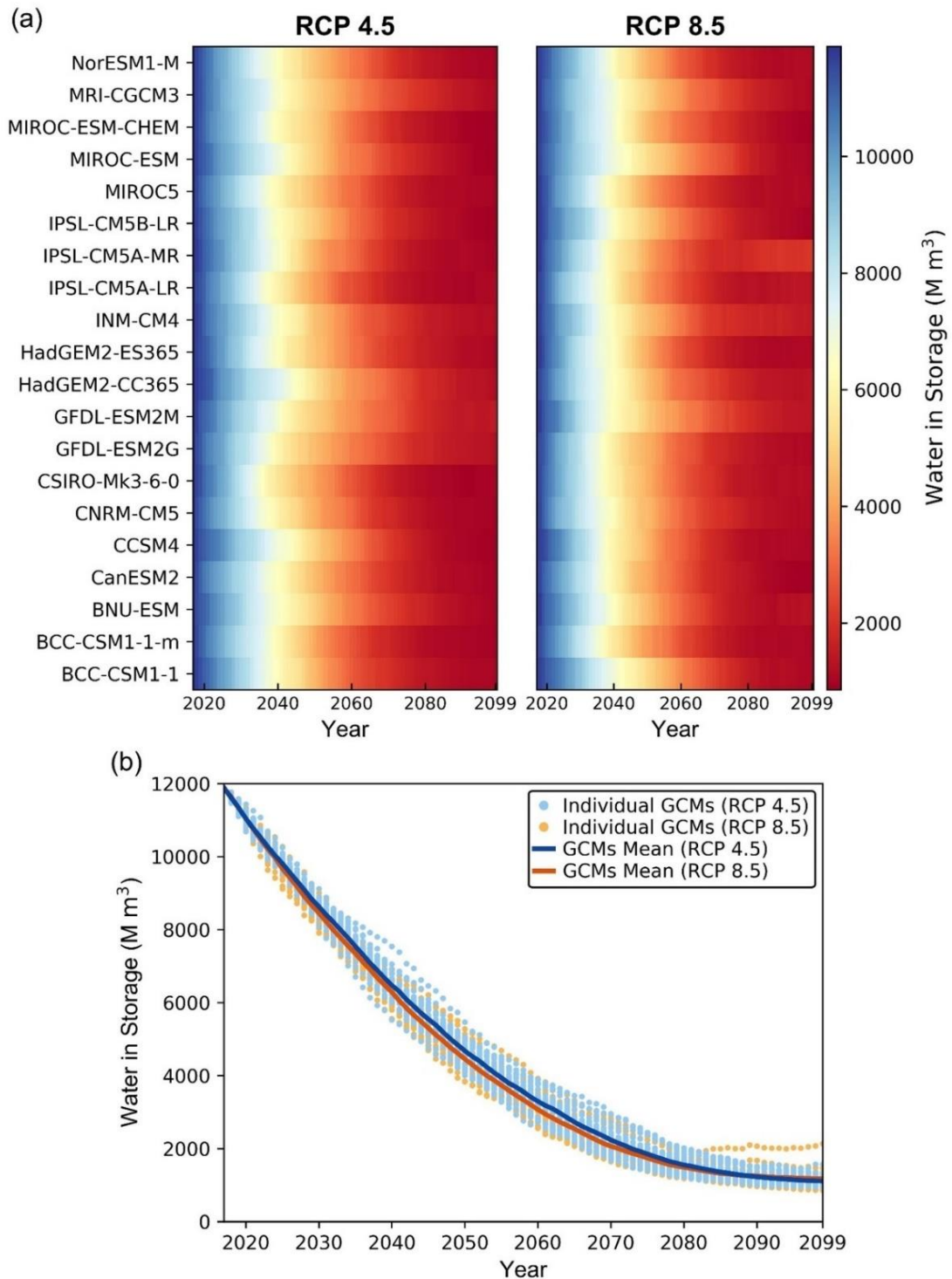


Figure 2.9. Total groundwater storage in Finney County projected from 2017 to 2099 under various climate scenarios. (a) Long-term groundwater depletion pathway for each climate scenario. (b) Total groundwater storage variations in different climate scenarios.

The ensemble means of projected groundwater storage values for RCP 4.5 and for RCP 8.5 imply that GHG emissions slightly affect groundwater availability in the study area (Figure 2.9b). This can be attributed to the fact that the negative impact of GHG emissions, which is manifested in decreasing trend of projected SPEI values for RCP 8.5, becomes significant in the second half of the century, that is to say in the years after 2040 (Figure 2.7b and c). By that time, total groundwater storage declines by more than 37% in all scenarios, indicating approximately half of the total volume loss occurs without being significantly affected by GHG emissions; moreover, extreme dry conditions in years after 2040 will not likely lead to drastic GWL declines because of groundwater withdrawal constraints caused by reduced well capacities.

To evaluate the impacts of climatological factors on groundwater availability in a spatially distributed manner, we analyze the rasters of projected saturated thickness from 2017 to 2099, obtained through running the RF model for different climate scenarios developed based on individual GCMs. In each year and for each RCP scenario, we compute the minimum, maximum, and ensemble mean of projected saturated thickness values at each grid cell (Figs. S4-S6 in Supplementary Material). The ensemble mean rasters of projected saturated thickness show the majority of the aquifer's domain in Finney County will become depleted (i.e., saturated thickness drops below 9 m) by 2060 in both RCP 4.5 and 8.5 scenarios (Figure 2.10a).

The minimum, maximum, and ensemble mean rasters of projected saturated thickness are used to estimate the aquifer's depletion time frame spatially by finding the first year when saturated thickness drops below 9 m at each cell (Figure 2.10b). The depletion time frame rasters clearly show the extent of impact of climatological factors on groundwater availability across the study area. The majority of the aquifer's extent in the county will become depleted by 2050, 2060, and

2070 under minimum, mean, and maximum saturated thickness conditions, respectively (in both RCPs).

To quantify the impact of climatological factors on groundwater depletion time frame, we calculate the difference of depletion time frames under minimum and maximum saturated thickness conditions for each RCP (Figure 2.10c); those regions that will become depleted after the projection period (i.e., years after 2099) are excluded from this spatial analysis. The results imply climate plays an important role in groundwater availability in regions with small saturated thickness and low well density, i.e., regions located along the already depleted areas on the northeast of the county; in these regions, climatological factors can shift the depletion time frame by more than 25 years. On the other hand, groundwater availability in the rest of the county (especially central and southern parts) with larger saturated thickness and higher well density is less affected by climate as a result of more intensive groundwater withdrawals. Overall, the depletion time frame in the majority of the study area will be shifted by 15 years or less (in both RCPs) due to uncertainties in future climatic variables. In this study, we ignore uncertainties in gridded saturated thickness data arising from interpolation errors.

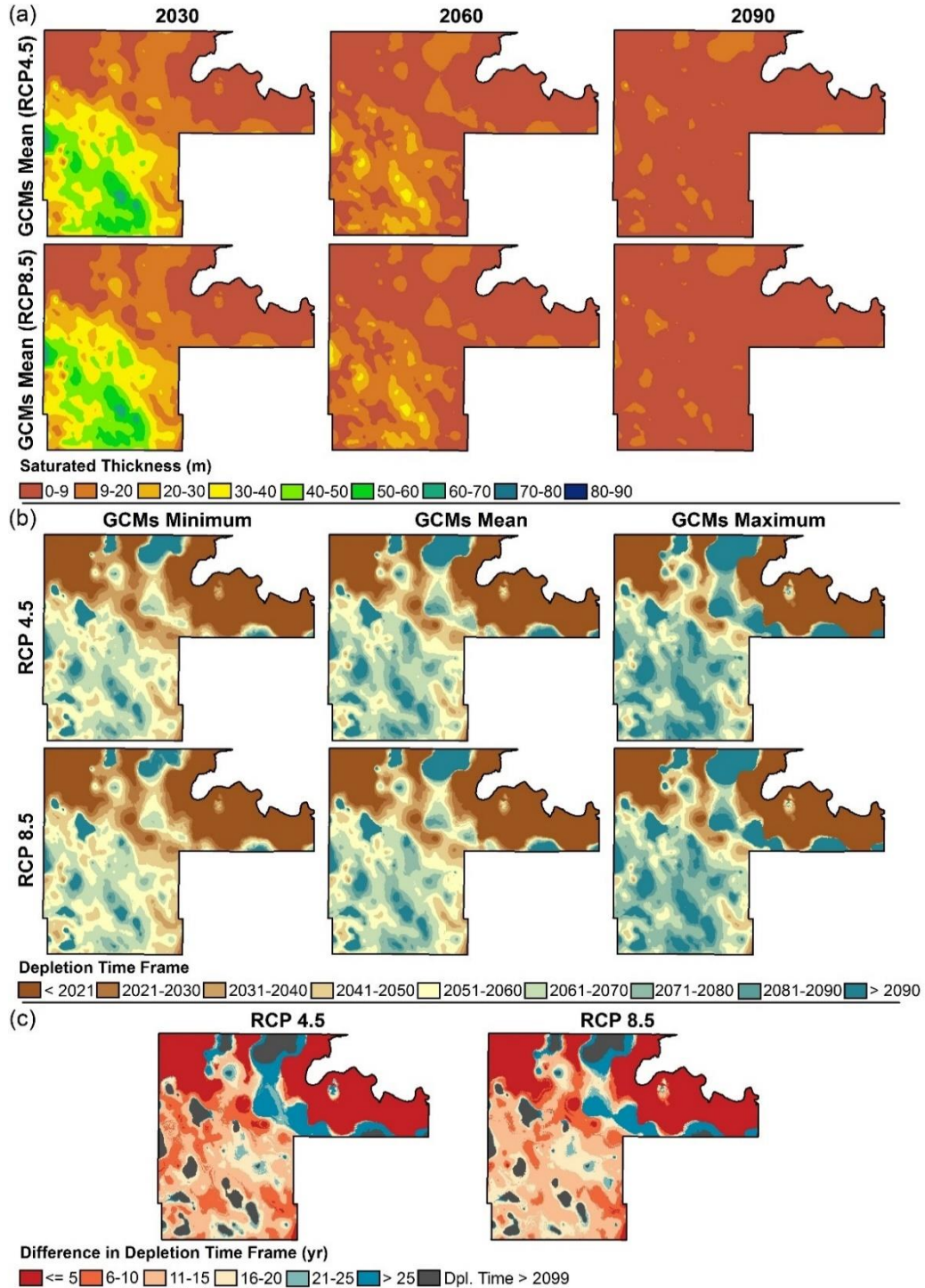


Figure 2.10. Long-term impacts of climatological factors on groundwater availability in Finney County. (a) Gridded data of the ensemble mean of projected saturated thickness values in 2030, 2060, and 2090. (b) Groundwater depletion time frames estimated based on the minimum (GCMs Minimum), ensemble mean (GCMs Mean), and maximum (GCMs Maximum) of projected saturated thickness values in each RCP. (c) Shifts in groundwater depletion time frames as a result of uncertainties in future climate projections.

2.3.2.3. Long-term Groundwater Level Projections under Several Combined Management and Climate Conditions

To assess and present the RF model's ability to properly capture well retirement effects under a variety of conditions, three GWL measurement points are selected and their saturated thickness variation in all scenarios is plotted (Figure 2.11). The results at point 1, where initial saturated thickness is large and retired wells density is high, show that the retirement plans significantly affect groundwater depletion trends and prolong the aquifer's lifetime; the higher the well retirement percentage the more positive impacts with respect to the aquifer's sustainability. On the other hand, at point 2 with similar initial saturated thickness value to point 1 but lower well retirement density, the impacts of the retirement plans on groundwater depletion become less significant. At both of these points, the effectiveness of the retirement plans diminishes under the RCP 8.5 ensemble mean climate scenario as a result of increase in the severity of dry events in years after 2040 due to the negative impact of GHG emissions (Figure 2.7b and c). At point 3, where initial saturated thickness is small and well retirement density is quite high, the retirement plans have negligible impacts on depletion trends in either climate scenario, emphasizing the importance of initial saturated thickness in conservation policies' success (Foster et al., 2017).

The impact of the well retirement plans on groundwater availability in the entirety of Finney County is inspected through computing total groundwater storage (see Eq. 4) from 2017 to 2099 in different management and climate scenarios (Figure 2.12a; see Figs. S7-S12 in Supplementary Material for projected saturated thickness rasters under different combined management and climate scenarios). The results show even with 50% well retirement, the aquifer will lose 87% and 93% of its total water in storage by the end of the century, under the RCP 4.5

ensemble mean and the RCP 8.5 ensemble mean climate scenarios, respectively; therefore, well retirement policies do not lead to sustained groundwater savings in the county.

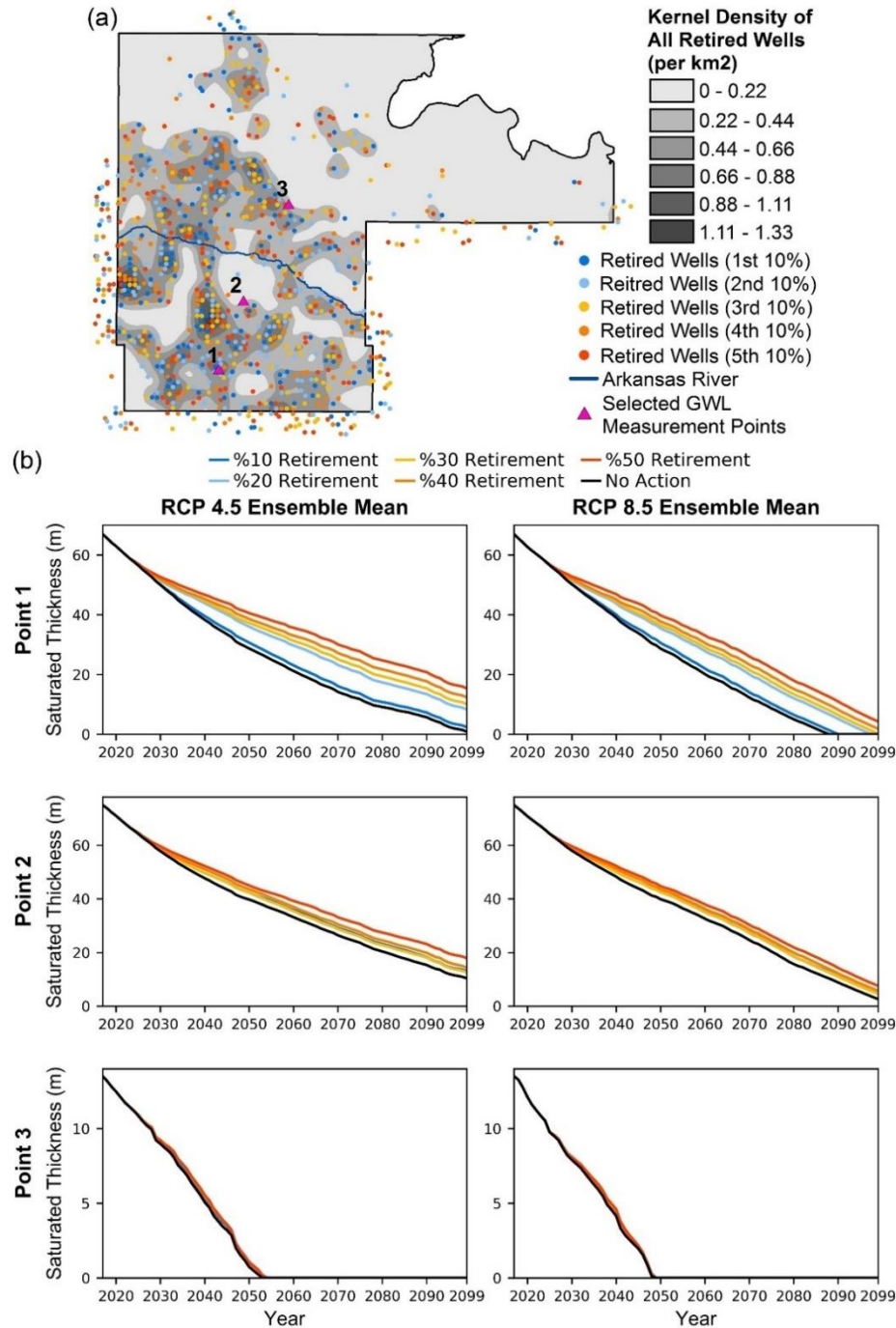


Figure 2.11. (a) Selected groundwater level (GWL) measurement points, 10%-clusters of candidate wells for retirement used to develop different retirement plans, and the kernel density of all retired wells (i.e., 50% retirement plan). (b) Projected saturated thickness values at the selected GWL measurement points and under a combination of six well retirement plans (including no-action scenario) and two climate scenarios (RCP 4.5 ensemble mean and RCP 8.5 ensemble mean) from 2017 to 2099.

To better understand and compare the temporal effects of the retirement plans on groundwater sustainability, total water saving in each scenario is computed as a percentage of total groundwater storage at the beginning of the projection period (Figure 2.12b). The groundwater saving period starts with the initiation of well retirements in 2021 and lasts until total water saving peaks in a year within the 2054-2065 period, depending on the retirement and climate scenarios. After hitting the peak, total water saving starts declining as a result of higher groundwater extraction rates in the retirement scenarios compared to the no-action scenario. In the second half of the century, groundwater depletion rate is higher in the retirement scenarios because of larger saturated thickness values. In other words, the producers who opt out of the retirement plans are given this opportunity to pump more water due to higher well capacities compared to the no-action scenario. The temporary efficacy of well retirement policies has been discussed by Rouhi Rad et al. (2021).

While for 10, 20, 30, 40, and 50% well retirement plans the maximum total water saving under the RCP 4.5 ensemble mean climate scenario is 1.6%, 3.6%, 5.7%, 8.2%, and 10.8%, respectively, it is 1.5%, 3.4%, 5.3%, 7.3%, and 9.5% under the RCP 8.5 ensemble mean climate scenario. These values indicate the negative impact of drier climate conditions on the outcomes of the well retirement plans. As mentioned before, the severity of dry events increases in years after 2040 in the RCP 8.5 ensemble mean climate scenario. At the same time, the implementation of the retirement plans leads to larger saturated thickness values across the county. The concurrency of both drier climate conditions and larger saturated thickness increases the groundwater depletion rate and reduces total water saving in the retirement plans.

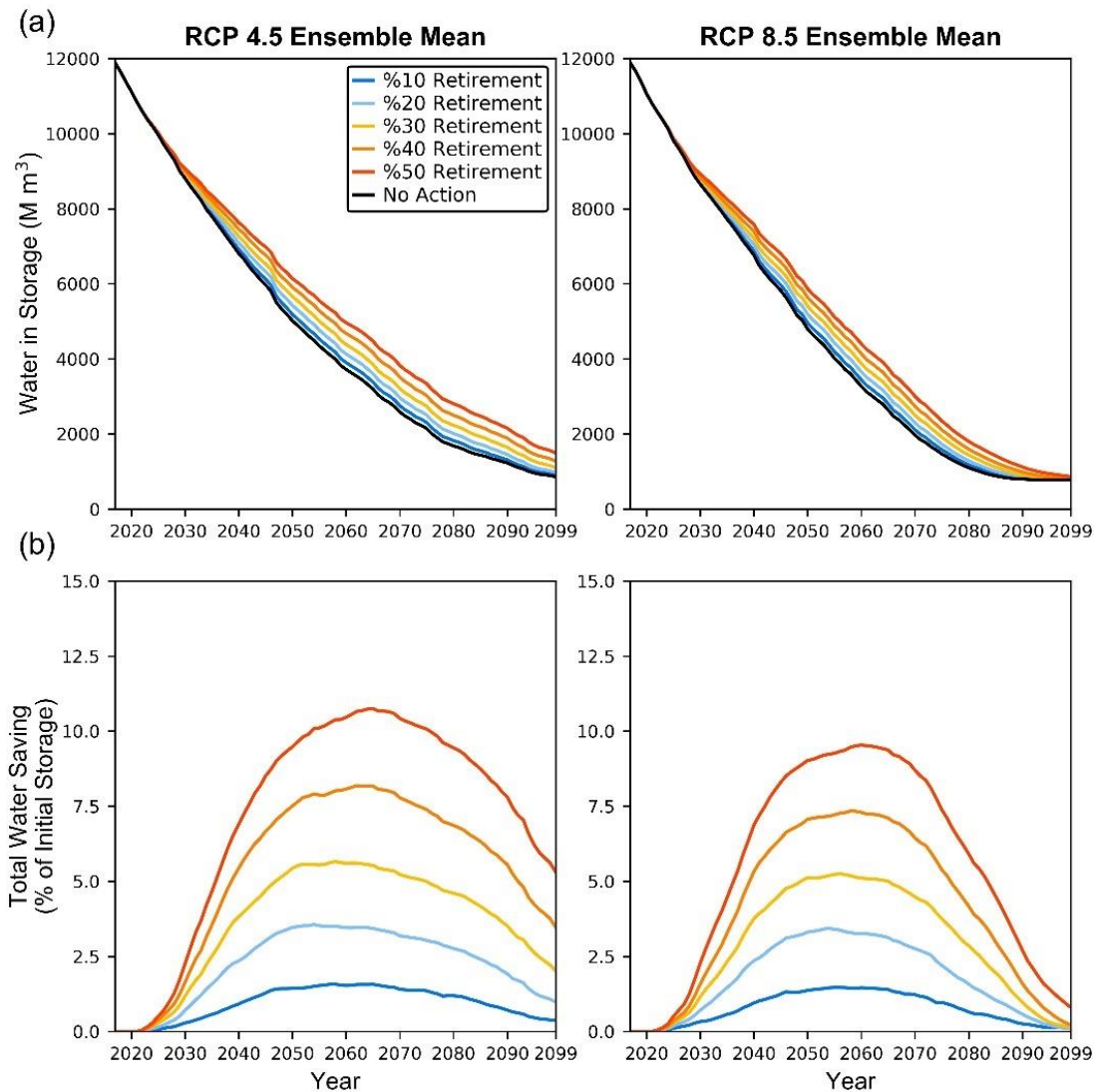


Figure 2.12. (a) Total groundwater storage in Finney County projected from 2017 to 2099 under a combination of six well retirement plans (including no-action scenario) and two climate scenarios (RCP 4.5 ensemble mean and RCP 8.5 ensemble mean). (b) Total water saving in each retirement scenario computed as a percentage of total groundwater storage at the beginning of the projection period.

2.4 Summary and Conclusions

The steady overexploitation of the Ogallala Aquifer over past decades has raised concerns about the viability of irrigated crop production in regions overlying the aquifer in the foreseeable future, particularly in the Southern and Central High Plains. Handling this issue in a proper manner requires an accurate, long-term groundwater level (GWL) forecasting tool. Here, we developed a

data-driven modeling framework utilizing the random forests (RF) technique in combination with ordinary kriging to spatiotemporally project future GWLs as a function of climatological and anthropogenic factors. The developed modeling framework was tested in Finney County in southwest Kansas, an intensively groundwater irrigated region with significant groundwater depletion in recent years.

In this study, rather than developing a separate model for each monitoring well, a single RF model was trained, calibrated, and tested using all historical GWL measurements across the study area. Initially, we considered nine input variables for the RF model based on the hydrogeological characteristics of the study area. The most relevant input variables were then selected through an iterative process, utilizing the RF algorithm to compute the relative importance of the variables. The final input variables are groundwater withdrawal potential (*GWWP*), mean SPEI-3 in irrigation period (*SPEI-IRR*), groundwater depth (*GWD*), water year total precipitation (*P*), mean SPEI-3 in water year (*SPEI-WY*), and aquifer specific yield at groundwater level (*Sy*). The introduction of *GWWP*, which is the product of saturated thickness and number of active high production wells, as a new measure of pumping intensity enables the RF model to capture decline in groundwater depletion rate as the system progresses towards aquifer depletion. *GWWP* also gives the RF model this ability to quantify the impacts of well retirement policies on future GWLs. Testing the generalization capabilities of the RF model from multiple aspects suggests the acceptable performance of the model, taking into account its simplicity with respect to development and calibration. The sensitivity analysis of the RF model reveals the dominance of *GWWP* over the rest of the input variables.

Simulation runs through the 21st century with climate impacts paint a dire picture of future groundwater availability in the study area under business as usual conditions. The majority of the

aquifer's extent will cease to support irrigated agriculture by 2050, 2060, and 2070 under the worst, average, and best climate conditions, respectively. The results imply that while climate significantly affects groundwater depletion trends in areas with small saturated thickness and low well density, climatological factors will likely shift the aquifer's depletion time frame by 15 years or less in most of the study area. Moreover, greenhouse gas emissions do not have a substantial impact on groundwater availability in the county.

Simulations including combined impacts of management and climate conditions indicate that although well retirement plans will lead to groundwater savings in the county, the savings do not persist for a long period due to larger groundwater withdrawals by the remaining wells. The results also suggest the efficacy of the retirement plans is hindered by drier climate conditions in the second half of the century as a result of GHG emissions.

Overall, the modeling framework developed in this study holds promise for capturing long-term climatological and regulatory impacts on groundwater availability in intensively irrigated regions. The modeling framework can serve as a rapid assessment tool, informing policymakers about future groundwater availability at the county level, and under different climate and management conditions. It helps policymakers to determine the urgency of adaptation and/or conservation strategies concerning groundwater depletion across the High Plains Region.

While finding the most suitable ML technique for long-term projection of GWLs is outside the scope of this study, replacing the RF method with more recent and well tested ML methods such as deep learning techniques (Zhang et al., 2018; Solgi et al., 2021) could further improve the modeling framework performance and should be considered in future studies. Another possible pathway to improved GWL projections would be the spatial clustering of GWL measurement points into homogenous groups (Nourani et al., 2022a). Then, instead of developing one single

model for all measurement points, a separate model would be developed for each cluster which could lead to more accurate forecasts. Since uncertainties in gridded data, such as saturated thickness and S_y , are ignored here, future work should seek to evaluate interpolation errors and their resultant impacts on model outputs.

CHAPTER 3.

DETAILS OF THE EASTERN COLORADO-NORTHWEST KANSAS GROUNDWATER MODEL

Highlights

In hydro-economic modeling of groundwater systems, the credibility of the outcomes is highly dependent on the groundwater model. However, previous studies have often overlooked the importance of employing appropriate groundwater models. The groundwater models incorporated in these studies are either overly simplistic or were designed for objectives other than hydro-economic modeling. This can result in lack of sufficient control over groundwater diversion and recharge for each irrigation well and associated irrigated parcel. In this study, we develop a groundwater model (MODFLOW) for a portion of the High Plains Aquifer in eastern Colorado and northwest Kansas. This model provides control over different aspects of the groundwater system required for integration with field-scale agronomic and economic models in a hydro-economic modeling framework. Given the substantial groundwater extraction for irrigation in the study area, we pay careful attention to the estimation of irrigation requirements. Notably, we develop a modified version of the model, MODFLOW-RS, which leverages remote sensing data to estimate groundwater extraction for irrigation. Our analysis indicates that both the MODFLOW and MODFLOW-RS models exhibit appropriate performance. However, the MODFLOW-RS model excels in simulating groundwater levels and changes.

3.1. Introduction

Since pioneering studies in the 1980s, hydro-economic models addressing groundwater systems have undergone significant enhancements in terms of their hydrologic component. Early models employed simplistic single-cell groundwater models with infinite hydraulic conductivity, known as bathtub models (Brill and Burness, 1994; Feinerman and Knapp, 1983; Gisser and Sánchez, 1980). Such models, however, can underestimate pumping externalities and the benefits of groundwater management (Brozović et al., 2010). Later models have evolved to include a spatially explicit representation of groundwater systems. Some apply Darcy's Law and mass balance equations directly to simulate groundwater flow and storage (Guilfoos et al., 2016, 2013), while others employ physically-based groundwater models wherein the mentioned equations are embedded (Hrozencik et al., 2017; Mulligan et al., 2014; Rouhi Rad et al., 2020b).

Despite recent advancements, many groundwater models incorporated in these studies are not appropriate for hydro-economic analysis; i.e., they either present oversimplifications (Guilfoos et al., 2016, 2013) or were initially constructed for purposes other than hydro-economic modeling (Hrozencik et al., 2017; Hu et al., 2015; Khan and Brown, 2019; Mulligan et al., 2014; Noël and Cai, 2017; Rouhi Rad et al., 2020b). Although using pre-existing groundwater models can expedite the development of hydro-economic models, it is crucial to recognize their limitations in terms of providing full control over various aspects of the groundwater system. For instance, these models often overlook the enhanced precipitation recharge in irrigated lands due to increased soil moisture (Cherry et al., 2020). Furthermore, a number of previous studies do not compute irrigation return recharge based on simulated irrigation volumes, instead relying on already specified values in the models (Hrozencik et al., 2017; Hu et al., 2015; Rouhi Rad et al., 2020b). These limitations can compromise the reliability of the hydro-economic models findings.

In this chapter, we provide the details of the Eastern Colorado-Northwest Kansas groundwater model (MODFLOW), which is developed with the aim of integration with field-scale agronomic and economic models. We start by discussing the hydrogeology of the model's extent and the administrative units present in the study area. Following that, we describe the process of acquiring and filtering recorded groundwater levels, as well as generating groundwater level rasters for the entire simulation period. These datasets are crucial for the construction and validation of the MODFLOW model. We then detail the model's structure and explain the procedures adopted to estimate groundwater extraction. We also introduce a modified version of the model, MODFLOW-RS, which utilizes remote sensing data to estimate groundwater extraction for irrigation purposes. Next, we discuss the model calibration and sensitivity analysis techniques. Finally, we evaluate and compare the performance of both the MODFLOW and MODFLOW-RS models.

3.2. General Information

The eastern Colorado-northwest Kansas groundwater model domain encompasses 20,928 km² of the High Plains Aquifer (HPA) extent within the Republican River Basin and the Smoky Hill River Basin (Figure 3.1a). The main constituents of the HPA in our study area, in stratigraphic order from oldest (deepest) to youngest (shallowest), are the Miocene Ogallala Formation, the Pleistocene unconsolidated alluvial deposits, and the Pleistocene/Holocene loess, aeolian sand, and valley-fill deposits (Topper et al., 2003). The Ogallala Formation along with the overlying Pleistocene unconsolidated alluvial deposits stores the primary portion of groundwater, which is generally under unconfined condition, in the HPA. The Ogallala Formation was formed by the deposition of sediments eroded from the alluvial fans fronting the modern Rocky Mountains and carried by the streams flowed towards the Great Plains (Topper et al., 2003).

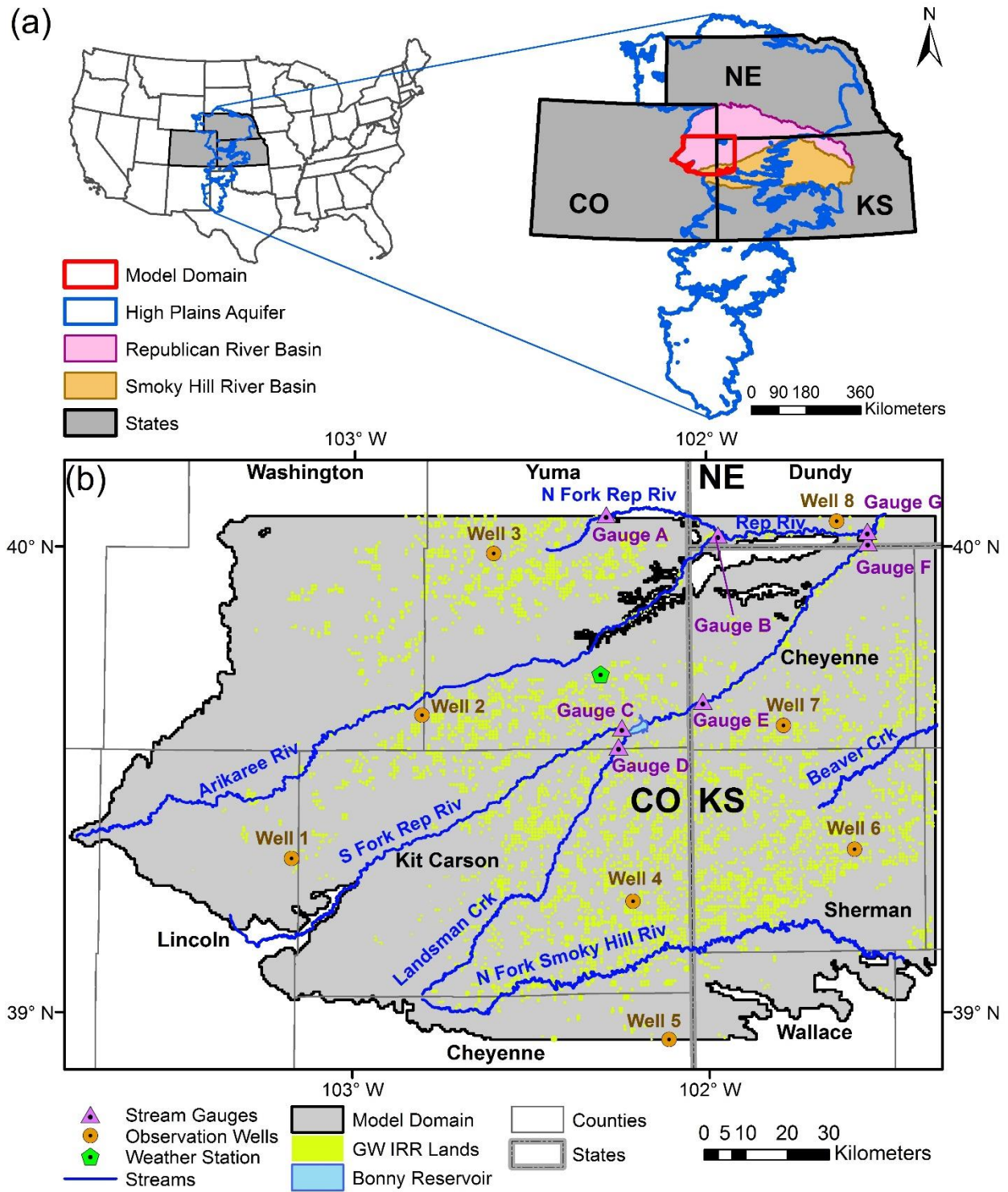


Figure 3.1. (a) Study area in relation to the High Plains Aquifer and major river basins. (b) MODFLOW model domain with groundwater-irrigated (GW IRR) lands.

The Mesozoic rocks, mainly the Upper Cretaceous Pierre Shale, underlie the HPA in our study area. Valley-fill deposits along the Arikaree River and its tributaries, the South Fork Republican River and its tributaries, the Republican River, the North Fork Smoky Hill River, and the Beaver Creek have formed the alluvial aquifers within the model domain. The alluvial aquifers are embedded within the Ogallala Formation and maintain a hydraulic connection to the underlying HPA, although in some regions the streams have downcut into the Pierre Shale.

The model domain covers the entirety of the HPA extent in Kit Carson and Lincoln counties, Colorado as well as Cheyenne and Sherman counties, Kansas. In addition, it includes considerable portions of the HPA within Washington and Yuma counties, Colorado. Moreover, it covers parts of the HPA in Cheyenne, Dundy, and Wallace counties in Colorado, Nebraska, and Kansas, respectively (Figure 3.1b).

The lateral boundaries of the HPA shape the western and the southeast edges of the model domain (Figure 3.1b). To delineate the western and southeast boundaries of the model domain, the geologic maps of the study area (U.S. Geological Survey, 2019a) were used to locate the regions where the Upper Cretaceous Pierre Shale crops out as a result of the HPA sediments erosion and downcutting. The Republican River reach between the outlets of the Arikaree River Watershed at Haigler and the South Fork Republican River Watershed near Benkelman in Nebraska forms the northern limit of the model domain.

The incorporation of the entirety of the South Fork Republican River watershed as well as Cheyenne and Sherman counties in Kansas was the main factor in positioning the eastern boundary of the model extent. The southern boundary is located based on the inclusion of the HPA's lateral boundaries as the southeast perimeter of the model domain. Regions within the model boundaries wherein streams have downcut into the Pierre Shale, such as areas along the Arikaree River and

its tributaries in Yuma County, Colorado and regions with very thin or absent water-bearing sediments, such as areas along the Kansas-Nebraska border (Prescott, 1953), are excluded from the model domain (Figure 3.1b).

3.3. Model Domain and Administrative Units

The model domain in Colorado is encompassed by the Northern High Plains Designated Groundwater Basin (DGB) and covers the whole area of the Arikaree and Plains and parts of the Central Yuma, East Cheyenne, and W-Y Groundwater Management Districts (GWMDs; Figure 3.2). In Colorado, designated groundwater is defined as that groundwater available in the eastern plains of Colorado where surface water is limited and groundwater establishes the primary source of water supply. To regulate and administer the designated groundwater resources, the Colorado Ground Water Commission established eight DGBs in the 1960s that are subdivided into 13 GWMDs.

In addition to Colorado, parts of the model domain are located within the Northwest Kansas Groundwater Management District (GMD) Number 4 and Nebraska's Upper Republican Natural Resources District (NRD; Figure 3.2). In Kansas, five GMDs were established in the 1970s in the western and central parts of the state to form local government units for the proper management of groundwater resources. Nebraska's NRDs were created in 1972 with the aim of establishing locally elected entities that would get involved in solving flood control, soil erosion, irrigation runoff, and groundwater quality and quantity issues across the state.

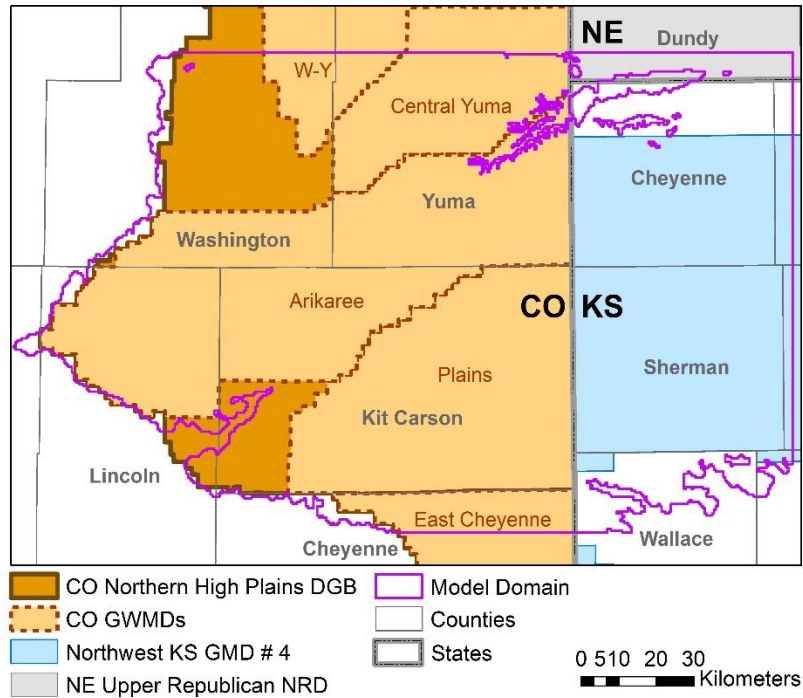


Figure 3.2. Model domain and administrative units, including Designated Groundwater Basins (DGBs) and Groundwater Management Districts (GWMDs) in CO, Groundwater Management Districts (GMDs) in KS, and Natural Resources Districts (NRDs) in NE.

3.4. Measured Groundwater Level Data

As an initial step, we had to collect measured groundwater level data, since they are required for model construction as well as model calibration. Groundwater level measurements in a total of 3448 wells located within the model domain and its immediate vicinity were obtained from the Colorado’s Decision Support Systems (CDSS; Colorado Water Conservation Board & Colorado Division of Water Resources, 2019), the WIZARD Water Well Levels Database (Kansas Geological Survey, 2019a), and the USGS National Water Information System (NWIS; U.S. Geological Survey, 2019d). The obtained measurements are spanning a period from 1923 to 2019 and were filtered for quality control in a three-step process suggested by Haacker et al. (2016). Subsequently, in wells with multiple records within a water year, we computed the average of

measurements for interpolation purpose. For calibration purpose, however, we kept two records; i.e., the one closest to October 1st and the one closest to April 30th, which are representing the minimum and maximum groundwater levels in a water year, respectively. Figure 3.3 displays the distribution of groundwater level measurement points within the model domain and the number of available records for model calibration and testing (Section 3.6).

To generate the rasters of measured groundwater level, we interpolated annual (water year) changes in groundwater levels using ordinary kriging with an exponential semivariogram model (Isaaks and Srivastava, 1989). For each water year, the raster of annual change in groundwater levels was added to the previous water year's groundwater level raster, producing the raster of measured groundwater level in the current water year at a resolution of 50 m $\times$ 50 m. The whole process was automated through a Python programming language script that employs the ArcPy package. To initiate this sequential process, we had to come up with a raster of groundwater table elevation that represents the predevelopment period. We compiled a dataset of the earliest groundwater level measurement recorded within a 3000-m search radius and assumed it represents the predevelopment state. The dataset was then detrended and interpolated in ArcMap using ordinary kriging with a Gaussian semivariogram model, resulting in a raster of predevelopment groundwater levels. Since the measurement records collected during the irrigation season (from May through September) were removed in the preprocessing procedure, the generated rasters represent quite static groundwater levels at the beginning of the irrigation season in each year.

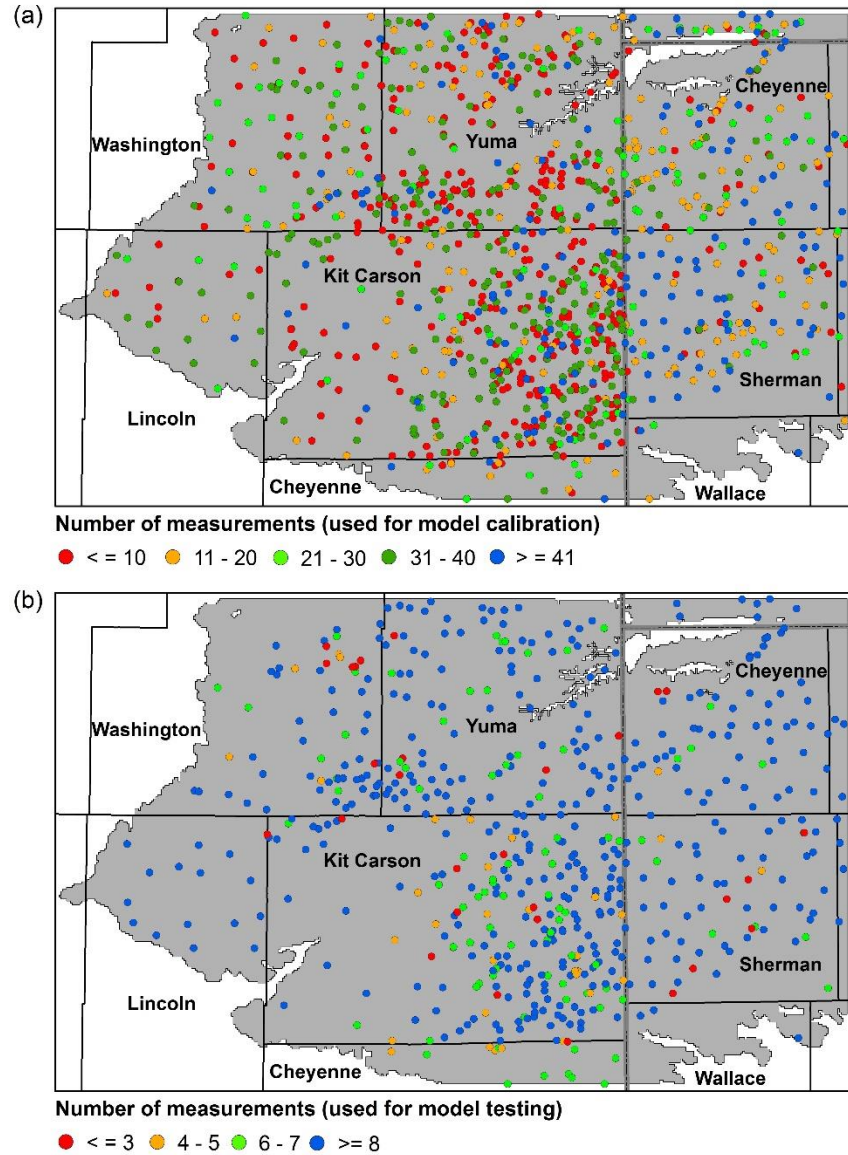


Figure 3.3. Groundwater level observation points within the model domain. (a) Points and the number of their records used for model calibration (from 1946 to 2010). (b) Points and the number of their records used for model testing (from 2010 to 2018).

3.5. Model Structure

The eastern Colorado-northwest Kansas groundwater model is constructed using the U.S. Geological Survey's modular three-dimensional finite difference groundwater flow model with a Newton formulation (MODFLOW-NWT, Niswonger et al., 2011). The Newton method is a

commonly used method for solving systems of nonlinear equations that is particularly useful in modeling groundwater systems involving drying and rewetting nonlinearities, such as heavily stressed unconfined aquifers and surface water-groundwater interactions. The eastern Colorado-northwest Kansas groundwater model (hereafter called the MODFLOW model) is discretized in the horizontal plane by constructing an orthogonal grid of uniform 500 m $\times$ 500 m cells that comprises 252 rows and 420 columns (Figure 3.4). There is no discretization in the vertical plane, since the MODFLOW model is a single-layer unconfined model similar to the most of the large-scale and regional-scale groundwater models constructed for the HPA to date (e.g., Liu et al., 2010; Peterson et al., 2016; Republican River Compact Administration, 2003). The MODFLOW model consists of 105,840 cells in total, including 83,713 active (variable head) cells and 22,127 inactive (no-flow) cells.

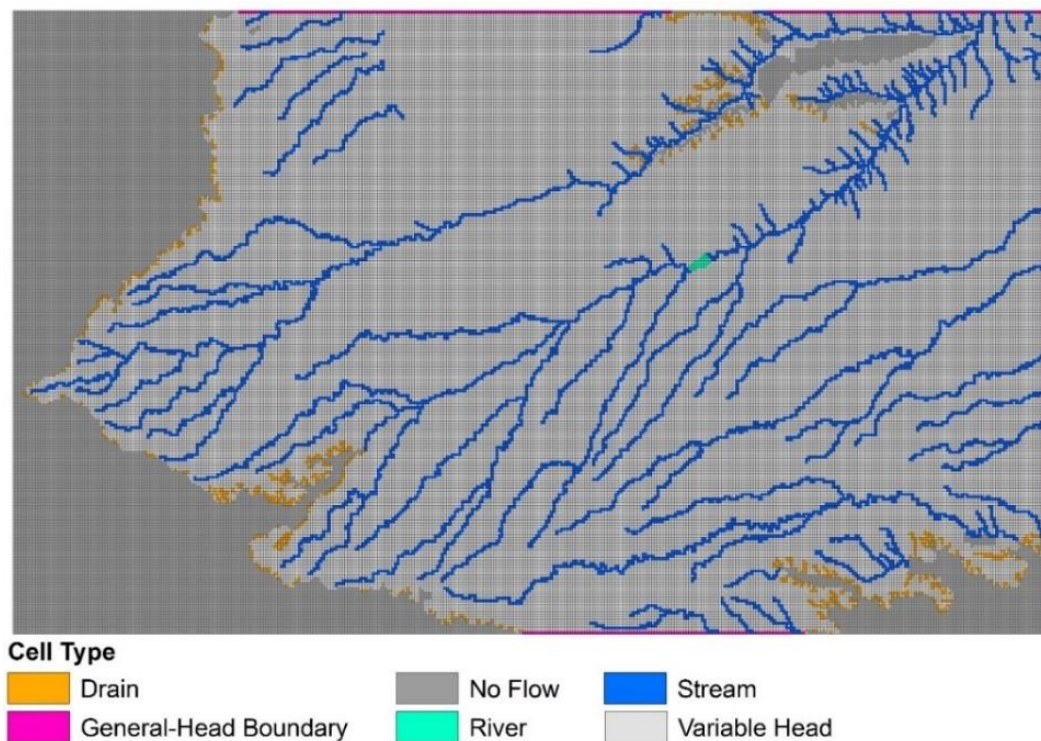


Figure 3.4. MODFLOW model configuration.

The simulation period is discretized through a sequence of MODFLOW models (Table 3.1): a steady-state model for the predevelopment period (before May 1st, 1946), followed by seven transient models for the period from May 1st, 1946 to September 30th, 2018. It is a standard practice in groundwater modeling to start simulation with a steady-state model that provides initial conditions (i.e., initial heads) for a subsequent transient model (Anderson et al., 2015). The hydrogeological properties of the aquifer such as effective horizontal hydraulic conductivity (K) and effective specific yield (S_y) change through time due to groundwater level variations (Section 3.5.3). Therefore, a sequence of transient models are constructed here to update K and S_y periodically. In this procedure, computed heads for the last time step of a given transient model are used as initial heads in the following model. The first transient model is spanning a longer period, as groundwater extraction is less intense in the early years and groundwater levels do not change rapidly compared to the rest of the simulation period.

Table 3.1. MODFLOW model temporal discretization.

Simulation Period	Simulation Type	Start Date	End Date	Number of Stress Periods	Number of Pumping Periods (May 1-Sep 30)	Number of Recovery Periods (Oct 1-Apr 30)	Number of Time Steps
Predevelopment*	Steady-state	NA**	NA	1	NA	NA	1
1946-1960	Transient	5/1/1946	4/30/1960	28	14	14	5114
1960-1970	Transient	5/1/1960	4/30/1970	20	10	10	3652
1970-1980	Transient	5/1/1970	4/30/1980	20	10	10	3653
1980-1990	Transient	5/1/1980	4/30/1990	20	10	10	3652
1990-2000	Transient	5/1/1990	4/30/2000	20	10	10	3653
2000-2010	Transient	5/1/2000	4/30/2010	20	10	10	3652
2010-2018	Transient	5/1/2010	9/30/2018	17	9	8	3075

* Before 5/1/1946

** Not Applicable

Since pumping for irrigation is the dominant stress in the MODFLOW model domain, each transient model incorporates two categorizes of stress periods: pumping stress periods spanning a

153-day period from May to September and recovery stress periods spanning a 212-day period or a 213-day period (in leap years) from October to April. In this work, a daily time step is selected for all stress periods to be able to couple the MODFLOW model with models providing outputs on a daily basis in the future. All the MODFLOW model input files are generated using FloPy (Bakker et al., 2016), which is a Python package for creating and post-processing MODFLOW models. The following subsections will detail the design features of the MODFLOW model.

3.5.1. Lateral No-flow Boundaries

The western and the southeast boundaries of the MODFLOW model domain are situated at the outcrops of the Pierre Shale (bedrock) and are simulated as lateral no-flow boundaries (Figure 3.4). Within the model domain, there are regions along the river valleys where the Pierre Shale crops out due to stream erosion. In addition, a region exists along the Kansas-Nebraska border where water-bearing sediments are either absent or negligible (Prescott, 1953). No-flow cells are placed at both of these internal regions, as well (Figure 3.4).

3.5.2. Lateral Flow Boundaries

The lateral boundary flows in the eastern, the northern, and the southern boundaries of the MODFLOW model domain are simulated using the General-Head Boundary (GHB) Package in MODFLOW (Harbaugh et al., 2000; Figure 3.4). Since there is no physical boundary such as major surface water features near the eastern, the northern, and the southern perimeters of the model domain, we tie these boundaries to measured groundwater heads outside the model boundaries. The rasters of measured groundwater head are annual and represent groundwater levels at the beginning of each irrigation season (Section 3.4). Therefore, specified boundary heads in the GHB cells are updated on an annual basis (i.e., every other stress period), while computed groundwater

heads in all the active model cells vary on a daily basis. This would lead to a reverse lateral groundwater flow at the time of peak drawdown; i.e., at the end of the pumping period and at the beginning of the recovery period. To avoid this problem, we set the specified head values in the GHB cells equal to the groundwater heads measured at a considerable distance of 5000 m from the cells.

The hydraulic conductance of the 5000-m interface between the GHB cell and the location of the measured groundwater head is computed using the harmonic mean approach (Harbaugh, 2005). We use calibrated K values (Section 3.5.3) for the calculation of the hydraulic conductance. Given the uncertainties in determining the hydraulic conductance values, we need to calibrate the hydraulic conductance for different perimeter boundaries of the model and in different stress periods. To do so, nine conductance adjustment factors are defined and estimated through model calibration (Table 3.2). For the years before 1960, one adjustment factor is considered for both the stress periods, since pumping is less intense in the earlier years and groundwater levels do not vary substantially throughout a year.

Table 3.2. Calibrated parameters for the General-Head Boundary (GHB) cells.

Parameter	Description	Calibrated Estimate	Unit
east_bnd_before_1960	Conductance adjustment factor for the eastern GHB cells in both stress periods during the years before 1960	1.25	NA
north_bnd_before_1960	Conductance adjustment factor for the northern GHB cells in both stress periods during the years before 1960	1.06	NA
south_bnd_before_1960	Conductance adjustment factor for the southern GHB cells in both stress periods during the years before 1960	0.75	NA
east_bnd_after_1960_sp1	Conductance adjustment factor for the eastern GHB cells in the recovery period during the years after 1960	1.23	NA
north_bnd_after_1960_sp1	Conductance adjustment factor for the northern GHB cells in the recovery period during the years after 1960	1.25	NA
south_bnd_after_1960_sp1	Conductance adjustment factor for the southern GHB cells in the recovery period during the years after 1960	1.00	NA
east_bnd_after_1960_sp2	Conductance adjustment factor for the eastern GHB cells in the pumping period during the years after 1960	1.16	NA
north_bnd_after_1960_sp2	Conductance adjustment factor for the northern GHB cells in the pumping period during the years after 1960	1.25	NA
south_bnd_after_1960_sp2	Conductance adjustment factor for the southern GHB cells in the pumping period during the years after 1960	0.96	NA

3.5.3. Hydrogeological Properties

To estimate the hydrogeological properties of the HPA within the MODFLOW model domain, namely bedrock elevation, effective horizontal hydraulic conductivity (K), and effective specific yield (S_y), we compiled a well log dataset incorporating 2191 boreholes in the model domain and its vicinity (Figure 3.5a). The boreholes data were retrieved from the well construction reports available in the CDSS, the Water Well Completion Records Database (WWC5; Kansas Geological Survey, 2019b), and the Nebraska Registered Groundwater Wells Database (Nebraska Department of Natural Resources, 2019a). The well logs were rigorously studied to determine the location of the Pierre Shale (bedrock) and its overlying unconsolidated lithology layers at every

borehole. The bedrock elevations were then detrended and interpolated in ArcMap using ordinary kriging with a tetraspherical semivariogram model, generating gridded estimates of bedrock elevation and depth to bedrock from the land surface (Figure 3.5b) at a resolution of $50 \text{ m} \times 50 \text{ m}$; the former one is used to compute the bottom elevation of the MODFLOW model cells. The depth to bedrock varies from 2 m in certain areas within the stream valleys and along the aquifer's lateral boundaries to over 65 m in the paleovalleys stretching northeastward, with an average of 58 m.

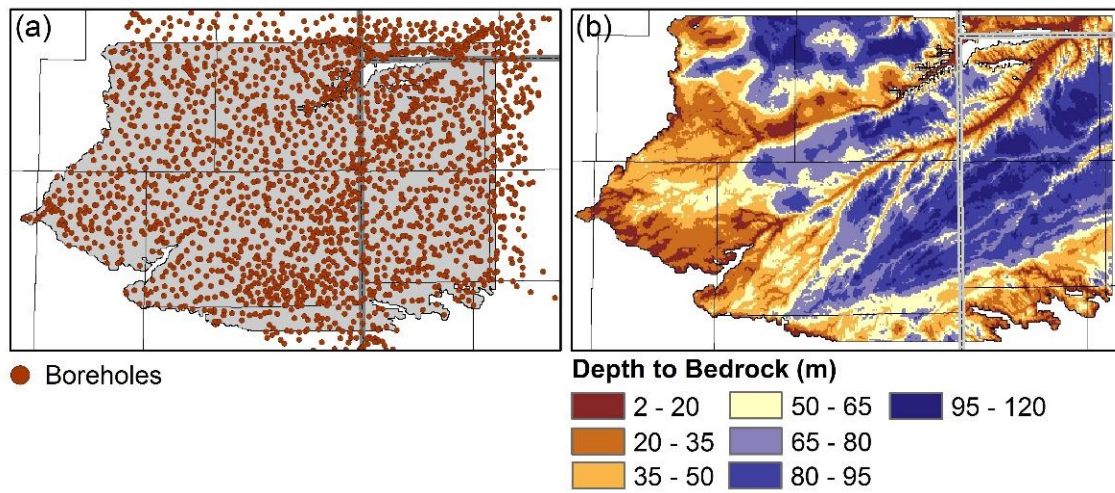


Figure 3.5. (a) Boreholes used for the estimation of bedrock elevation, horizontal hydraulic conductivity, and specific yield in the MODFLOW model domain and its immediate vicinity. (b) Depth to bedrock from the land surface.

The well log dataset was further leveraged to estimate effective K and S_y spatiotemporally, following the procedure proposed by Liu et al. (2010). In this procedure, we first extract the value of the measured groundwater level rasters (Section 3.4) at the location of every borehole during each simulation period (Table 3.1). For the predevelopment period, however, there is only one measured groundwater level at each borehole, since the system is at a steady state; moreover, effective S_y is not estimated for this period. Subsequently, we calculate weighted average K and S_y values at each borehole for different simulation periods using the extracted groundwater levels.

To estimate the effective K at a given borehole in the predevelopment period, we calculate the thickness-weighted average K value of all the lithology layers located between the groundwater level and the bedrock (Figure 3.6a).

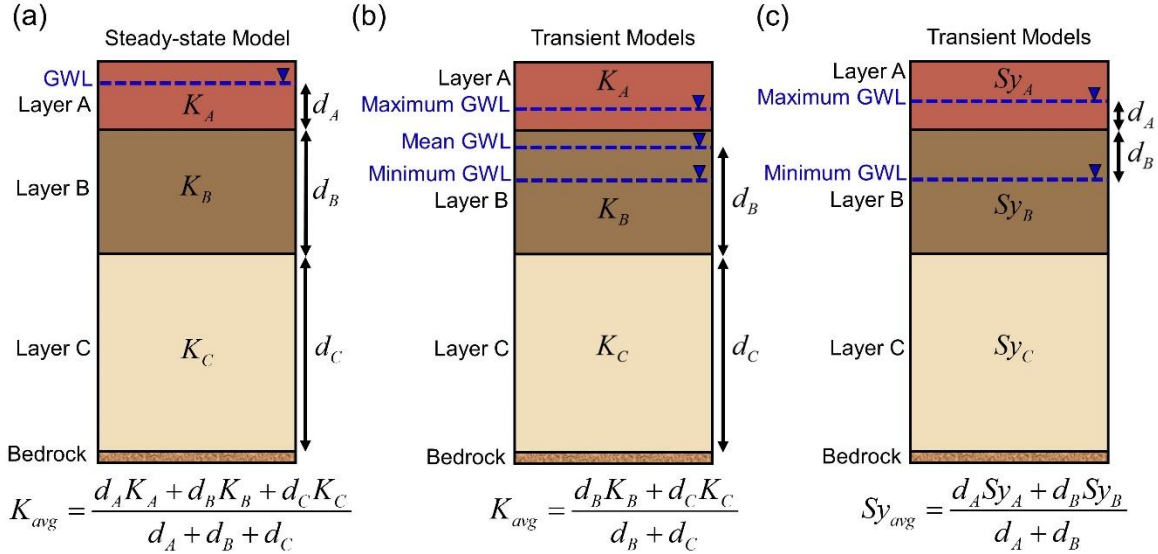


Figure 3.6. Graphical illustration of hydrogeological properties calculation as a function of groundwater level (GWL) for different MODFLOW models. (a) Effective horizontal hydraulic conductivity (K) calculation for the steady-state model. (b) Effective K calculation for the transient models. (c) Effective specific yield (Sy) calculation for the transient models.

For any simulation period other than the predevelopment period, the effective K at a given borehole is computed as the thickness-weighted average K value of all lithology layers from the mean groundwater level over that period to the bedrock (Figure 3.6b). Additionally, the effective Sy at a given borehole in each period is calculated by getting the thickness-average Sy value of all the lithology layers located between the maximum and the minimum groundwater levels during that period (Figure 3.6c). Finally, the effective K and Sy values computed at borehole locations are interpolated using ordinary kriging with a spherical and an exponential semivariogram model, respectively. The gridded estimates of effective K and Sy generated with a resolution of $200 \text{ m} \times 200 \text{ m}$ are used to compute K and Sy values in the MODFLOW model cells (Figures 3.7 and 3.8).

In this procedure, all lithology classifications are divided into seven groups of K values and five groups of S_y values and the value of each group is estimated through model calibration (Table 3.3). Although the effective K and S_y values estimated through this procedure are prone to inaccuracies associated with the approximate representation of lithology layers in well log data (Butler et al., 2020b), they are more physically reliable compared to the values estimated by conventional methods, such as the zonal and the pilot point approaches. Additionally, the spatial distribution of effective K and S_y values (Figures 3.7 and 3.8) agrees quite well with the values estimated before (McGuire et al., 2012; Peterson et al., 2016; Topper et al., 2003). The whole procedure is carried out through a set of Python programming language scripts employing the ArcPy package.

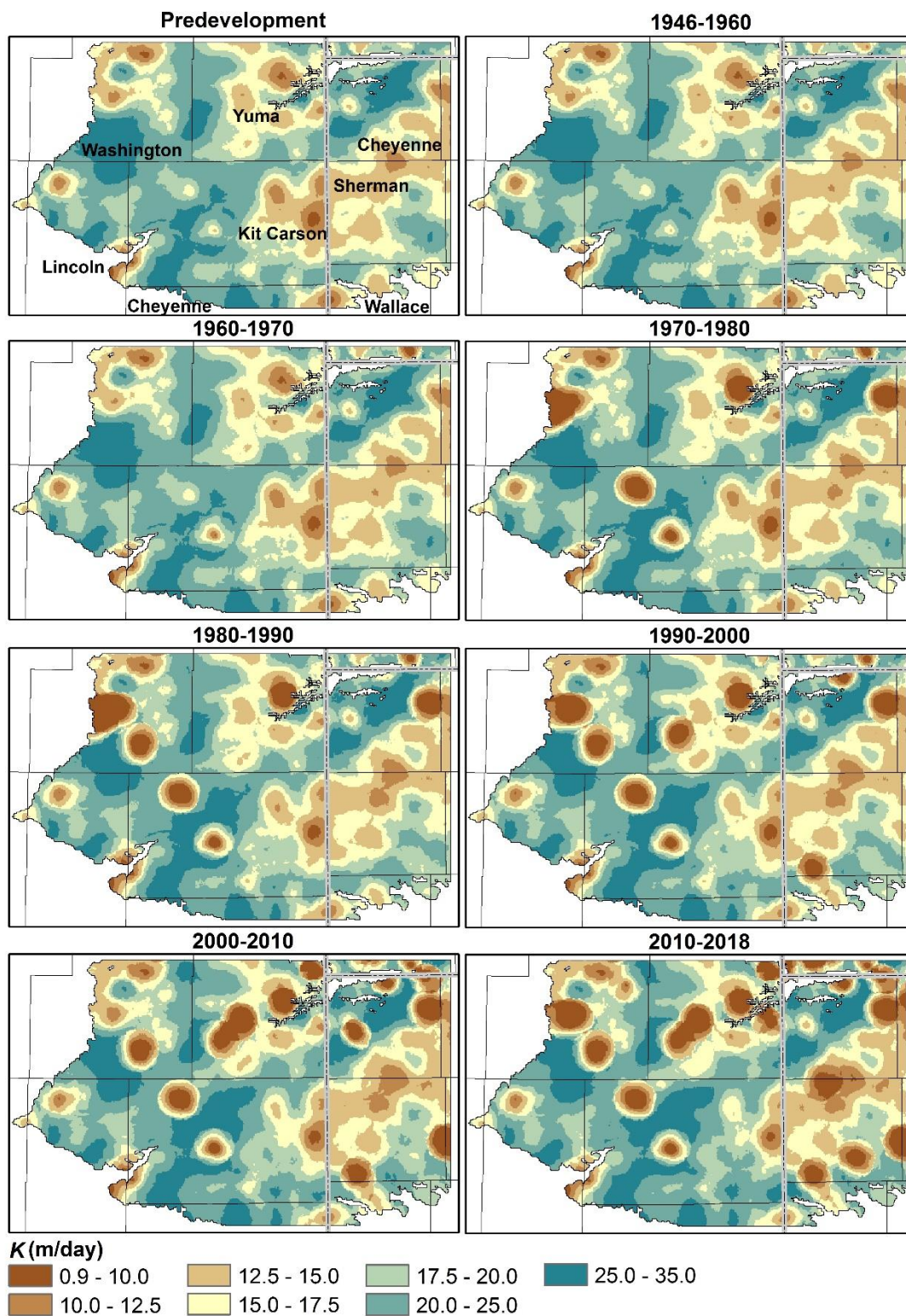


Figure 3.7. Calibrated effective horizontal hydraulic conductivity (K) values in the MODFLOW model cells during different simulation periods.

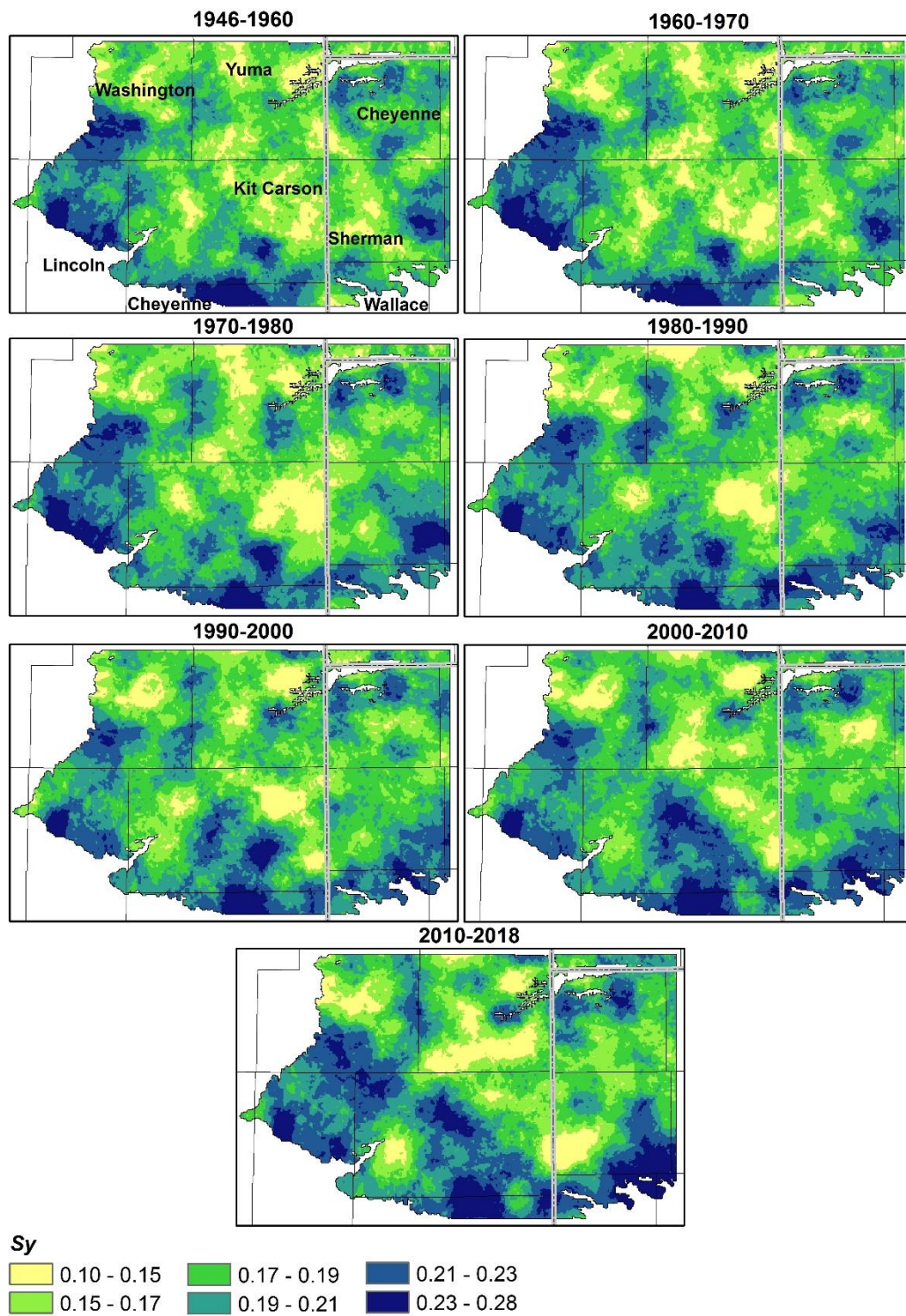


Figure 3.8. Calibrated effective specific yield (S_y) values in the MODFLOW model cells during different simulation periods.

Table 3.3. Calibrated horizontal hydraulic conductivity (*K*) and specific yield (*Sy*) values for different lithology classifications

Parameter	Lithology Classifications	Calibrated Estimate	Unit
<i>K1</i>	shale, clay, and siltstone	6.10E-05	m/day
<i>K2</i>	silty clay, sandy clay, clayey silt, silt, limestone/caliche, gypsum, and topsoil	5.69E-03	m/day
<i>K3</i>	sandy silt, gravelly clay, and sandstone	2.60E-02	m/day
<i>K4</i>	clayey sand, silty sand, and cemented sand and/or gravel	0.45	m/day
<i>K5</i>	fine sand and fine to medium sand	12.76	m/day
<i>K6</i>	sand, medium sand, coarse sand, fine to coarse sand, medium to coarse sand, clayey gravel, and silty gravel	26.70	m/day
<i>K7</i>	gravel and sand and gravel	41.49	m/day
<i>Sy1</i>	shale, clay, and siltstone	0.03	NA
<i>Sy2</i>	silty clay, sandy clay, clayey silt, silt, limestone/caliche, gypsum, topsoil, sandy silt, gravelly clay, and sandstone	0.10	NA
<i>Sy3</i>	clayey sand, silty sand, and cemented sand and/or gravel	0.22	NA
<i>Sy4</i>	fine sand, fine to medium sand, sand, medium sand, fine to coarse sand, medium to coarse sand, and clayey gravel	0.29	NA
<i>Sy5</i>	coarse sand, silty gravel, sand and gravel, and gravel	0.27	NA

3.5.4. Groundwater Extraction

3.5.4.1. System Condition during the Predevelopment Period

The predevelopment period represents the period before May 1st, 1946, wherein groundwater withdrawal is insignificant across the MODFLOW model domain and the groundwater system is at a steady state; i.e., inflows and outflows are in equilibrium and groundwater levels are constant in time. This period is simulated using a steady-state model, and the model outputs show the system condition prior to substantial groundwater withdrawals (Figure 3.9). Computed groundwater levels suggest a regional northeastward groundwater flow within the model domain (Figure 3.9a). Additionally, the presence of water table contour lines pointing in the upstream direction at their intersection with the streamlines is indicative of gaining streams.

The depth to water table from the land surface varies from nearly 0 m in certain areas within the river valleys to 86 m with an average of 36 m (Figure 3.9b). The aquifer saturated thickness (i.e., vertical distance from water table to bedrock) ranges from less than 5 m in regions along the lateral boundaries of the aquifer to over 50 m in some thick pockets located within Kit Carson, Washington, and Yuma counties in Colorado as well as Cheyenne and Sherman counties in Kansas (Figure 3.9c). On average, the saturated thickness is 22 m.

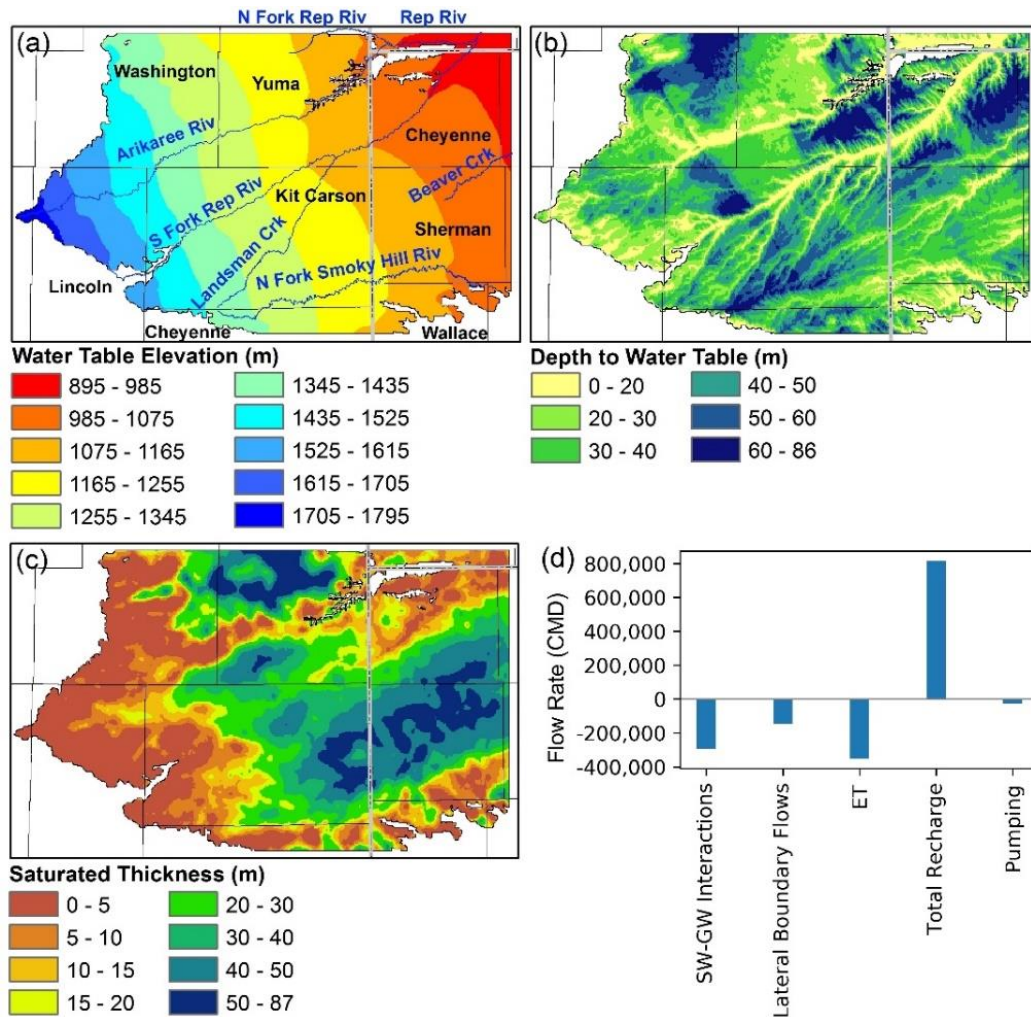


Figure 3.9. System condition during the predevelopment period simulated by the steady-state MODFLOW model. (a) Water table elevation. (b) Depth to water table. (c) Aquifer saturated thickness. (d) Groundwater budget (SW and GW are abbreviations that stand for surface water and groundwater, respectively).

The simulated groundwater budget for the predevelopment period (Figure 3.9d) indicates that evapotranspiration, net surface water-groundwater interactions, and net lateral boundary flows are the main outflow components of the system, which are balanced by the total recharge. The total recharge is the sum of precipitation recharge and irrigation return recharge (Section 3.5.6). The calculated total recharge value for the predevelopment period is equivalent to an annual recharge of 14 mm that is uniformly distributed across the entire model domain.

3.5.4.2. History of Groundwater Development

To study the history of groundwater development in the MODFLOW model domain, we first investigated the water right, well permit, and well construction documents and records available in the CDSS, the Water Information Management and Analysis System (WIMAS; Kansas Geological Survey, 2019c), the WWC5, and the Nebraska Registered Groundwater Wells Database. As a result of this effort, a dataset was created that contains valuable information on all the wells drilled within the model domain, including construction and plugging dates, use made of water, well capacity, maximum annual volume of appropriation, authorized maximum pumping rate, and authorized irrigated acreage. The dataset includes a total of 12,832 wells, categorized as follows: 4,531 for domestic use, 4,038 for irrigation, 3,565 for livestock, 524 for commercial purposes (including concentrated animal feeding operations), 87 for municipal use, and 40 for other purposes (Figure 3.10a).

Additionally, we located all irrigated parcels, both active and abandoned, across the model domain using the NAIP aerial imagery (from 2004 to 2015; U.S. Department of Agriculture, 2019c), the Landsat Legacy satellite images (from 1978 to 1999; Earth Resources Observation and Science (EROS) Center, 2019), and old aerial photographs (before 1975; U.S. Geological Survey, 2019b). Subsequently, we manually drew the parcel polygons and linked them to their

corresponding irrigation wells using the information available in the CDSS and WIMAS. We learned that there were 220,074 ha of irrigated lands within the model domain, with 99.6% using groundwater for irrigation and only 0.4% relying on surface water.

Data analysis reveals that groundwater development for irrigation purposes began in the 1940s through the digging of shallow wells primarily along streams, which were tapping the underlying alluvial aquifer. In the 1950s, advancements in drilling technology allowed for the construction of deeper wells in areas further away from the streams. With the advent of center pivot irrigation systems, groundwater development increased drastically during the 1960's and 1970's and by 1981, the number of active irrigation wells had reached its peak at 3,881 (Figure 3.10b). After this period, the number of active irrigation wells remained quite constant until the mid-2000's, when a total of 218 irrigation wells were retired in Colorado between 2005 and 2011 under the Agricultural Water Enhancement Program (AWEP), the Environmental Quality Incentives Program (EQIP), and the Conservation Reserve Enhancement Program (CREP). Since then, there have been no significant changes in the number of active irrigation wells. Figure 3.10b also shows the historical trend of groundwater development for non-irrigation uses.

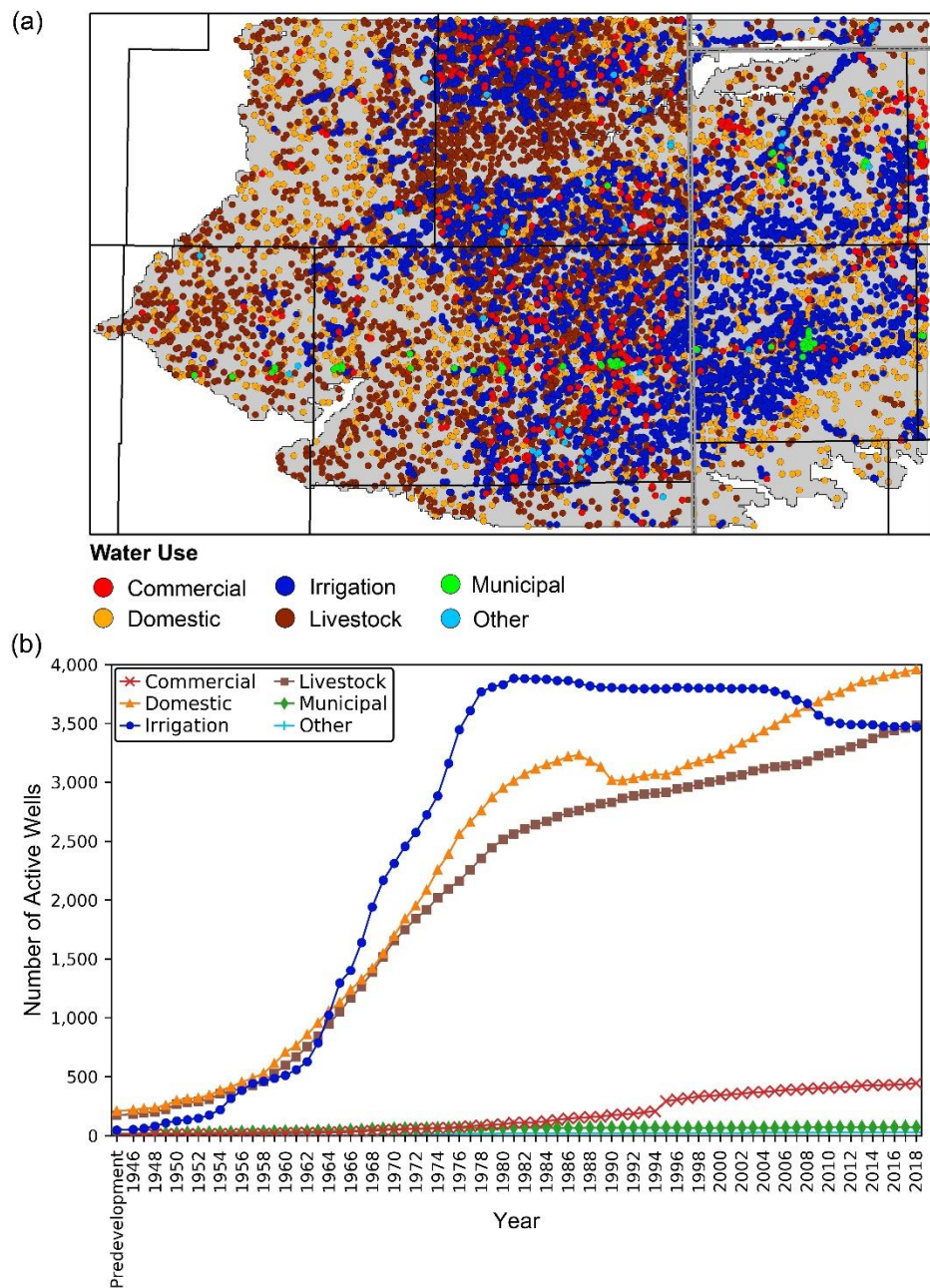


Figure 3.10. Groundwater development in the MODFLOW model domain (a) All wells that were operational at any point during the simulation period. (b) Number of active wells during the simulation period.

3.5.4.3. Estimation of Groundwater Withdrawals

Groundwater extraction through irrigation wells was estimated by computing the irrigation requirements in parcels irrigated using groundwater. To determine the irrigation requirement, we computed the net irrigation requirement (I_{net}) for corn and winter wheat, the two most prevalent crops in the study area, in every irrigated parcel as follows:

$$I_{net} = ET_c - P_e \quad (3.1)$$

where ET_c is the crop evapotranspiration computed using the FAO-56 method (Allen et al., 1998) and P_e denotes the effective precipitation estimated using the USDA-SCS method (Soil Conservation Service, 1970). In order to calculate ET_c , we initially obtained the latitude, longitude, and altitude of the irrigated parcels. We also identified the dominant soil type in each parcel and determined the hydrologic properties of the dominant soil using the Soil Survey Geographic Database (SSURGO; Natural Resources Conservation Service, 2019). Moreover, we collected daily weather records for the 1946-2018 period, including precipitation, minimum temperature, maximum temperature, relative humidity, wind speed, and solar radiation, which were measured at the nearest weather station to each irrigated parcel. With these data, we computed the daily reference evapotranspiration (ET_o) for every parcel using the FAO Penman-Monteith equation (Allen et al., 1998). The daily ET_c for each crop in each parcel was then calculated based on the daily ET_o :

$$ET_c = K_c ET_o \quad (3.2)$$

where K_c is a coefficient that incorporates both crop characteristics and averaged effects of evaporation from the soil. K_c varies throughout the growing period and is determined through

the construction of the crop coefficient curve (Allen et al., 1998). We then computed monthly ET_c and subsequently calculated monthly P_e as a function of monthly precipitation, monthly ET_c , and soil water storage factor (Soil Conservation Service, 1970). Next, we used the monthly values of ET_c and P_e for corn and winter wheat in Equation 3.1 to obtain monthly I_{net} values. Finally, we calculated the annual I_{net} for each crop in every irrigated parcel during the 1946-2018 period by summing the monthly I_{net} values. The results of our calculation indicate that the average annual I_{net} for corn and winter wheat across the irrigated parcels during this period was 385 mm and 295 mm, respectively. Figure 3.11 shows considerable variation in the annual I_{net} between a dry year (2002) and a wet year (2009), in terms of total precipitation. To estimate the annual I_{net} for each crop in the predevelopment period, we calculated the average of the annual I_{net} values during the 1946-2018 period.

For the majority of the simulation period, the specific crops planted in the irrigated parcels are unknown. Therefore, the annual I_{net} for a given parcel is calculated by taking a weighted average of the annual I_{net} for the major crop types that have been planted in the irrigated parcels in recent years:

$$\bar{I}_{net} = 0.70 (I_{net})_{corn} + 0.17 (I_{net})_{winter\ wheat} + 0.13 (I_{net})_{fallow} \quad (3.3)$$

where $\bar{I}_{net}$ is the weighted average annual net irrigation requirement, while $(I_{net})_{corn}$, $(I_{net})_{winter\ wheat}$, and $(I_{net})_{fallow}$ represent the annual net irrigation requirement for corn, winter wheat, and fallow, respectively. Since no water is applied to the land during fallow periods, $(I_{net})_{fallow}$ is equal to zero. The weights used in Equation 3.3 were computed based on the crop types that were planted in the irrigated parcels between 2008 and 2018, as determined using the NASS Cropland Data Layers (CDL; Boryan et al., 2011; U.S. Department of Agriculture, 2019b).

During this period, corn, winter wheat, and fallow collectively accounted for over 80% of the total area in the irrigated parcels.

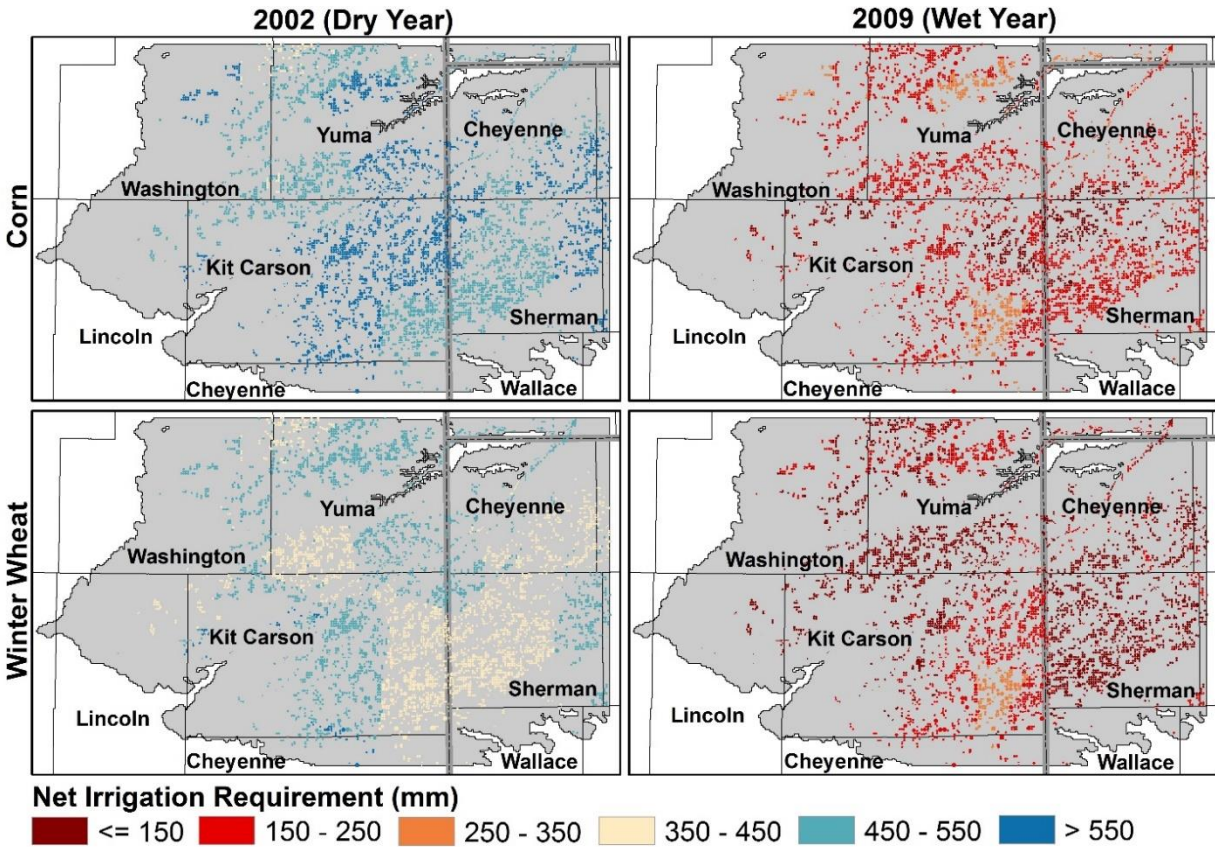


Figure 3.11. Comparison of net irrigation requirements (I_{net}) for corn and winter wheat in groundwater irrigated parcels in 2002 (a dry year) and 2009 (a wet year).

In order to improve the accuracy of irrigation requirement estimates, we implemented an additional step and utilized the annual rasters of irrigated lands over the HPA from 1984 through 2017, generated using remote sensing data and classification techniques (Deines et al., 2019). We first analyzed the irrigated lands rasters to determine the irrigation status of irrigated parcels between 1984 and 2017. Subsequently, we substituted Equation 3.3 with the following equation to calculate the weighted average annual I_{net} for each parcel:

$$\bar{I}_{net} = \begin{cases} 0, & \text{not irrigated} \\ 0.80 (I_{net})_{corn} + 0.20 (I_{net})_{winter\ wheat}, & \text{irrigated} \end{cases} \quad (3.4)$$

where $\bar{I}_{net}$ represents the weighted average annual net irrigation requirement, while $(I_{net})_{maize}$ and $(I_{net})_{winter\ wheat}$ correspond to the annual net irrigation requirement for corn and winter wheat, respectively. As with Equation 3.3, the weights in Equation 3.4 were calculated based on the crops grown in irrigated parcels during the 2008-2018 period. Equation 3.4 does not include the fallow term, in contrast to Equation 3.3, because we know the irrigation status of every parcel from 1984 through 2017. For years outside of the 1984-2017 period, we used Equation 3.3 to compute weighted average annual I_{net} in each parcel. In this study, the utilization of remotely sensed data to estimate irrigation requirements in irrigated parcels has resulted in a modified version of the MODFLOW model referred to as the MODFLOW-RS model from here on.

Following the calculation of $\bar{I}_{net}$, we computed the annual total irrigation requirement (I_{total}) for each parcel as follows:

$$I_{total} = \frac{\bar{I}_{net}}{E} \quad (3.5)$$

where E represents the irrigation efficiency (as a fraction between 0 and 1) that depends on the type of irrigation system used in each parcel (Table 3.4). In the Kansas region of the study area, data on the type of irrigation system is available in the WIMAS for years after 1990. However, in the Colorado region, information on irrigation systems is limited to 2010, 2015, and later years, which can be obtained from the CDSS. Moreover, there is no information available on the type of irrigation systems used in the Nebraska region. For areas and periods where irrigation system data is not available, we analyzed the NAIP aerial imagery, the Landsat Legacy satellite images, and old aerial photographs to estimate the approximate time of shift, if any, from flood to

center pivot irrigation systems at each irrigated parcel based on the shape of the parcel. Figure 3.12a displays the percentage of irrigated lands using each irrigation system from 1950 to 2018. The plot indicates that the center pivot system gained the major share of irrigated lands in the late 1980's. We have assumed that in years before 1950, flood irrigation was the only irrigation system available in the region.

Table 3.4. Irrigation efficiency and irrigation return flow for different irrigation systems.

Irrigation System	Irrigation Efficiency (%)*	Irrigation Return Flow (%)**
Center Pivot Conventional	80	9
Center Pivot LEPA	85	7
Center Pivot and Flood	70	17
Flood	60	25
Sprinkler (other than center pivot)	75	9
Subsurface Drip	95	4
Surface Drip	90	4

* Source of data is Irmak et al. (2011).

** Source of data is Liu et al. (2010).

According to the irrigation system data in Kansas, there was a shift from conventional center pivot systems to Low Energy Precision Application (LEPA) center pivot systems between 1991 and 2018 (Figure 3.12b). Since the type of center pivot systems in Colorado and Nebraska is unknown, we calculated a weighted average E for center pivot systems in these states based on the percentage of conventional and LEPA center pivots in Kansas, assuming a similar trend. We have assumed all center pivot systems in the study area were conventional before 1991. In addition to I_{total} , the type of irrigation system determines the amount of irrigation return recharge (Table 3.4 and Section 3.5.6.2).

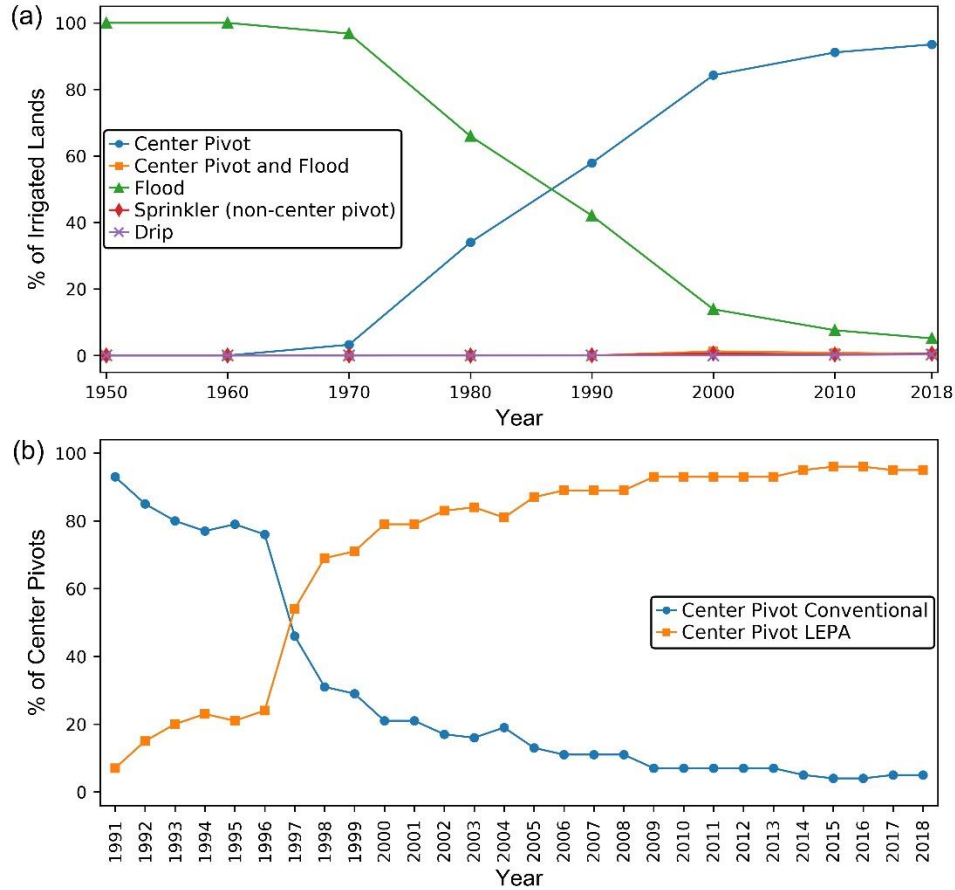


Figure 3.12. Historical variation of irrigation systems in the MODFLOW model domain. (a). Percentage of irrigated lands using each irrigation system. (b). Percentage of conventional and Low Energy Precision Application (LEPA) center pivot systems in the Kansas region.

We estimated the total volume of water applied to each groundwater irrigated parcel annually by multiplying I_{total} by the parcel area. Next, we divided the estimated volume equally among all wells irrigating the parcel to obtain the annual volume of pumped water for each irrigation well. The resulting annual volume of pumped water was divided by the length of pumping stress periods (153 days) to obtain the pumping rate for each irrigation well. In this procedure, we considered the values of maximum annual volume of appropriation and authorized maximum pumping rate as upper bounds for the estimated values of annual volume of pumped water and pumping rate, respectively. In addition, it was assumed that irrigation wells were shut

down during recovery stress periods. For the predevelopment period, which only has one stress period, we divided the annual volume of pumped water by 365 (the length of a year).

To calculate the pumping rate of non-irrigation wells, we divided the maximum annual volume of appropriation for each well by the number of days in a year (365 or 366), assuming that these wells operate year-round. The estimated pumping rate values for both irrigation and non-irrigation wells are incorporated into the Well (WEL) Package of MODFLOW (Harbaugh et al., 2000) to simulate groundwater extraction. It is important to note that in this study, we have estimated two sets of pumping rate values for irrigation wells during the 1984-2017 period: one without using remotely sensed data (incorporated in the MODFLOW model) and one with the use of remotely sensed data (incorporated in the MODFLOW-RS model).

3.5.5. Evapotranspiration

We use the Evapotranspiration (EVT) Package in MODFLOW to simulate evapotranspiration (ET) from the groundwater table (Harbaugh et al., 2000). We used the raster of measured groundwater levels in the predevelopment period (Section 3.4) to identify areas where depth to water table was less than 12 m (Figure 3.13). These identified areas are presumed to be locations where ET from the water table could occur, and they are mainly located within riparian zones. The rationale behind selecting a threshold of 12 m was to account for the uncertainties in the gridded estimate of predevelopment groundwater levels, given an extinction depth (rooting depth) of 2 m. The elevation of the ET surface was assumed to be equal to the land surface elevation, and the maximum ET flux for each stress period was calculated by taking the difference between potential and actual ET (Wei and Bailey, 2019), which were obtained from the TerraClimate dataset (Abatzoglou et al., 2018). Since TerraClimate data cover the period from

1958 through 2019, we computed the maximum ET rate for stress periods before 1958 by averaging data from the first 10 years of the dataset (1958-1967).

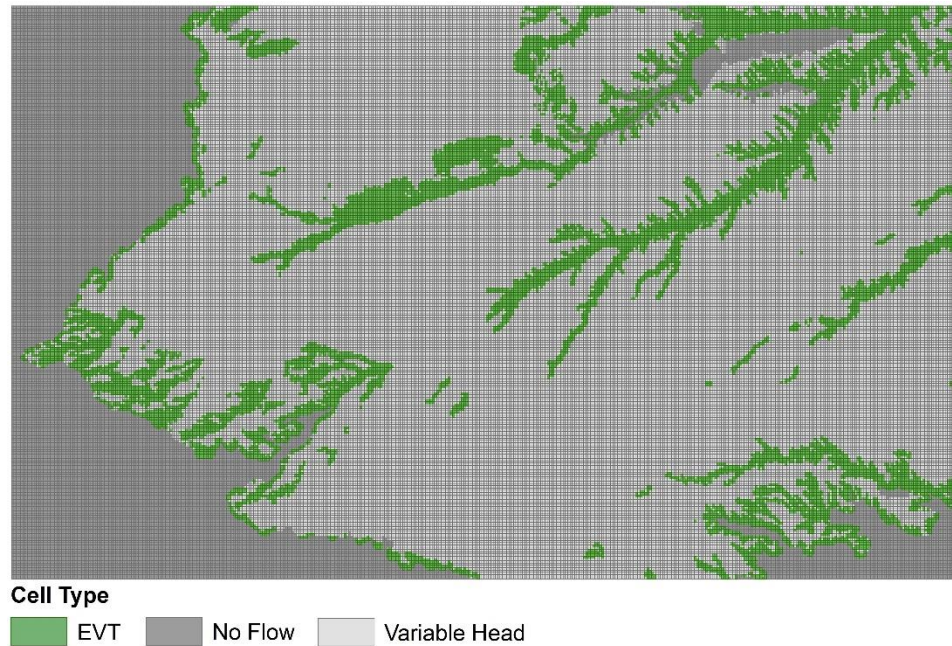


Figure 3.13. Evapotranspiration (EVT) cells in the MODFLOW model domain.

3.5.6. Recharge

We use the Recharge (RCH) Package in MODFLOW to simulate the total recharge to the groundwater table (Harbaugh et al., 2000). With the RCH Package, the total recharge is modeled as a specified flux distributed over the top of the cells in the MODFLOW model. For each stress period, the total recharge is computed as the summation of precipitation recharge and irrigation return recharge in each cell. Here, we explain how the values of precipitation recharge and irrigation return recharge were estimated. It is important to note that we assumed there is no delayed recharge in the study area when estimating both precipitation recharge and irrigation return recharge values.

3.5.6.1. Precipitation Recharge

To estimate the annual precipitation recharge in each model cell as a function of annual precipitation, we have used the method proposed by Liu et al. (2010), which involves a power function:

$$R = \begin{cases} 0, & P < P_0 \\ a(P - P_0)^b, & P \geq P_0 \end{cases} \quad (3.6)$$

where R represents the annual precipitation recharge to the groundwater table for a given model cell in a given water year, P is the total precipitation within the same model cell and water year, P_0 is the threshold precipitation depth after which recharge occurs, a is the coefficient term, and b is the power term. To compute the total precipitation for each model cell and water year, we used gridded estimates of monthly precipitation (PRISM Climate Group, 2019) across the MODFLOW model domain. To account for variations in soil properties and their impact on precipitation recharge, we have divided the model domain into four recharge zones (Figure 3.14a), using the hydrologic soil group classifications from SSURGO. The four recharge zones are alluvium, fine soil, medium soil, and coarse soil, which correspond to hydrologic soil groups D, C, B, and A, respectively. We then estimated the values of a , b , and P_0 for each zone through model calibration (Table 3.5). Figure 3.14b shows the calculated annual precipitation recharge in different recharge zones using Equation 3.6 with calibrated parameters for a range of annual precipitation values. The average annual precipitation within the model domain between 1946 and 2018 is 435 mm, resulting in annual precipitation recharge values of 0.21 mm, 3.61 mm, 17.62 mm, and 34.32 mm for the alluvium, fine soil, medium soil, and coarse soil zones, respectively. The negligible amount of recharge in the alluvium zone, where bedrock is so shallow, is probably due to the rejected recharge phenomenon.

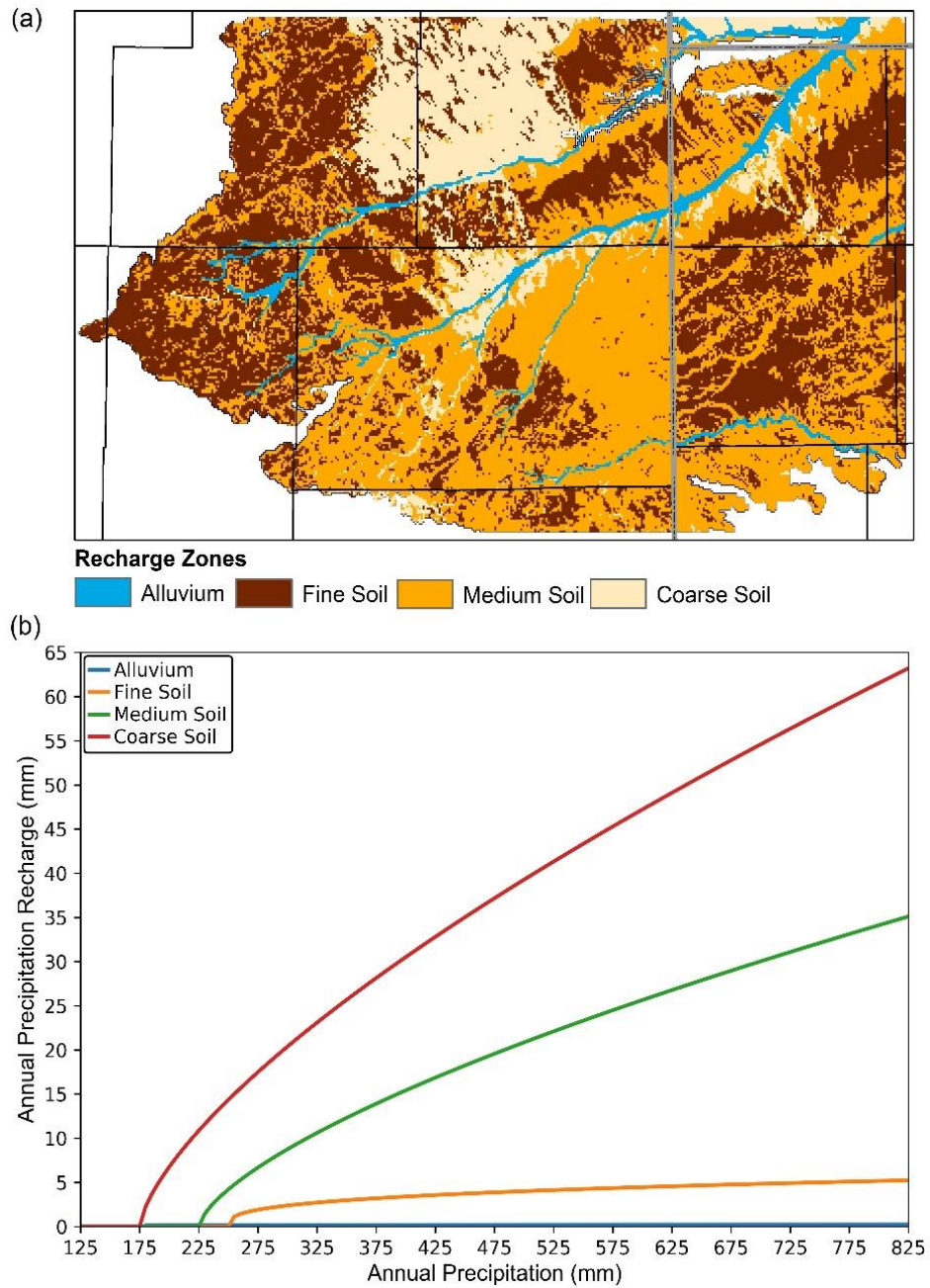


Figure 3.14. (a) Different precipitation recharge zones in the MODFLOW model domain. (b) Calibrated precipitation recharge curves for non-irrigated lands in different recharge zones.

Table 3.5. Calibrated parameters for precipitation recharge.

Parameter	Description	Calibrated Estimate	Unit
<i>a</i> _alluvium	Coefficient of the recharge function for the alluvium zone	0.10	NA
<i>b</i> _alluvium	Power of the recharge function for the alluvium zone	0.13	NA
<i>P0</i> _alluvium	Recharge threshold in the recharge function of the alluvium zone	175.00	mm
<i>a</i> _fine	Coefficient of the recharge function for the fine-textured soil zone	0.68	NA
<i>b</i> _fine	Power of the recharge function for the fine-textured soil zone	0.32	NA
<i>P0</i> _fine	Recharge threshold in the recharge function of the fine-textured soil zone	250.00	mm
<i>a</i> _medium	Coefficient of the recharge function for the medium-textured soil zone	0.49	NA
<i>b</i> _medium	Power of the recharge function for the medium-textured soil zone	0.67	NA
<i>P0</i> _medium	Recharge threshold in the recharge function of the medium-textured soil zone	225.00	mm
<i>a</i> _coarse	Coefficient of the recharge function for the coarse-textured soil zone	0.74	NA
<i>b</i> _coarse	Power of the recharge function for the coarse-textured soil zone	0.69	NA
<i>P0</i> _coarse	Recharge threshold in the recharge function of the coarse-textured soil zone	175.00	mm
enhncmnt_factor	Precipitation recharge enhancement factor for irrigated lands	2.88	NA

To divide annual precipitation recharge values between corresponding pumping and recovery stress periods, we apportioned them proportionally based on the total precipitation in each stress period. For the predevelopment period, we calculated the annual precipitation recharge using the average annual precipitation from 1895 to 1945 (51 years). In irrigated lands, given higher soil moisture levels, a greater portion of precipitation infiltrates into the soil and eventually reaches the groundwater table as recharge, compared to non-irrigated lands (Cherry et al., 2020). To account for the increased precipitation recharge in irrigated areas, we introduced a “precipitation recharge enhancement factor”. In these areas, for the pumping stress periods, we multiplied precipitation recharge by this factor, which was determined through model calibration (Table 3.5). As irrigation impacts the amount of precipitation recharge, two sets of precipitation recharge values have been estimated for model cells during the 1984-2017 period: one set that does not use remotely sensed irrigated lands data (incorporated in the MODFLOW model) and another that uses such data (incorporated in the MODFLOW-RS model).

3.5.6.2. Irrigation Return Recharge

During each irrigation event, a portion of the water applied leaves the root zone and reaches the groundwater table as recharge through deep percolation. The amount of water that reaches the groundwater table through irrigation depends on several factors, including the amount of water applied, soil types in the root zone and vadose zone, distribution of soil moisture within the root zone and vadose zone, depth of the water table, and type of irrigation system employed. In this study, however, we focus solely on the influence of the amount of water applied and the type of irrigation system on the value of irrigation return recharge.

In section 3.5.4.3, we calculated the annual total irrigation requirement (I_{total}) for each irrigated parcel using Equation 3.5. Additionally, we determined the type of irrigation system used for each parcel in each year. With I_{total} and the irrigation system type known, we computed the irrigation return recharge by multiplying I_{total} with the irrigation return flow percentage listed in Table 3.4 for the corresponding irrigation system. Due to the lack of specific data on the type of center pivot systems in Colorado and Nebraska, we estimated the shift from conventional to LEPA center pivot systems in these states. We did this by determining a weighted average irrigation return flow percentage for the center pivot systems, drawing from the observed proportion of conventional to LEPA center pivots in Kansas (Figure 3.12b) and assuming a similar trend. We have assumed all center pivot systems in the study area were conventional before 1991.

Note that we only considered irrigation return recharge during pumping stress periods, as no irrigation occurs during recovery stress periods. Similar to the precipitation recharge, two sets of irrigation return recharge values have been estimated for model cells from 1984 through 2017: one set that does not use remotely sensed irrigated lands data in the calculation of I_{total} (incorporated in the MODFLOW model) and another that uses such data (incorporated in the

MODFLOW-RS model).

3.5.7. Surface Water Features

3.5.7.1. Streams

To simulate stream-aquifer interactions, we use the Stream (STR) Package in MODFLOW (Prudic, 1989; Figure 3.4). The STR cells were placed using the National Hydrography Dataset Plus High Resolution (NHDPlus HR; Moore et al., 2019). According to this dataset, streams in the northwest of the MODFLOW model domain are not connected to downstream reaches due to truncation by a region with closed depressional areas. The STR Package instantaneously routes the baseflow through a stream network and can calculate stream stage in every reach, assuming a rectangular cross-section for streams and using the Manning formula. The width and slope of the stream reaches were estimated using the NAIP aerial imagery and the land surface elevation data (U.S. Geological Survey, 2019d), respectively. The specified Manning's roughness coefficient for all the stream reaches is 0.04, which corresponds to the normal value for clean and winding natural streams with some pools and shoals (Chow, 1959).

The STR Package requires sources and sinks in a stream network for each stress period to accurately route the baseflow. Significant sources within the model domain include releases from the Bonny Reservoir (Zone 14 in Figure 3.15) and inflows from the North Fork Republican River at the Colorado-Nebraska border, the Buffalo Creek near Haigler in Nebraska, and the Rock Creek at Parks, Nebraska (all shown as inflow stream gauges in Figure 3.15). The primary sinks consist of water diversions from the stream network through 14 irrigation ditches and 25 river pumps (Figure 3.15).

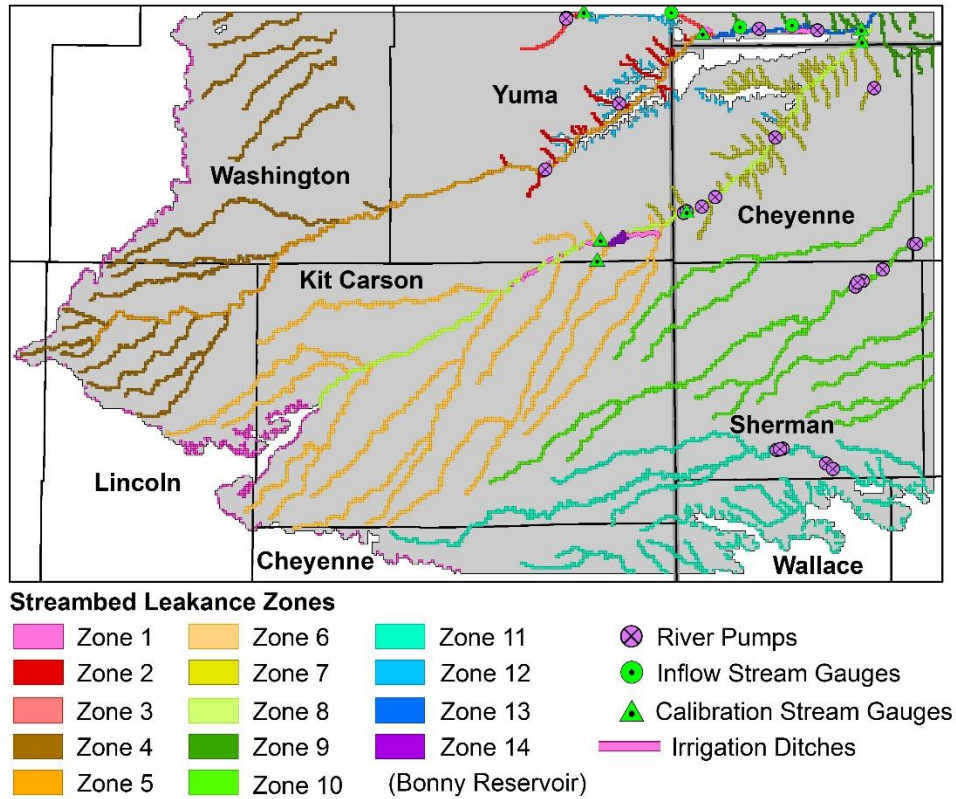


Figure 3.15. Surface water features incorporated in the MODFLOW model.

The Bonny Reservoir monthly outflow data stored in the HYDROMET (Bureau of Reclamation, 2019) were used to compute average water release for each stress period. Additionally, we derived daily discharge data at the inflow stream gauges from the NWIS (U.S. Geological Survey, 2019b) and employed the Baseflow Filter Program (Arnold et al., 1995; Arnold and Allen, 1999) to estimate daily baseflows at each gauge. Estimated daily baseflows were then used to compute average inflows in each stress period. Average diversion values in each stress period were estimated using surface water rights data and their historical diversion records available in the CDSS, the WIMAS, and the Nebraska Surface Water Rights Database (Nebraska Department of Natural Resources, 2019b).

In the STR cells, the elevation of the streambed's top is set to the average land surface

elevation where the stream line is located. The elevation of the streambed's bottom is determined by calibrating the depth to bottom value (Table 3.6). One main advantage of using the STR package in regions with intermittent streams, like our study area, is that leakage stops in a STR cell if the streamflow becomes zero and the groundwater head drops below the streambed's top elevation. Using the calibrated streambed vertical leakance values for different zones (Figure 3.15 and Table 3.6), we computed the streambed hydraulic conductance in the STR cells. This leakance represents the vertical hydraulic conductivity of the streambed sediments divided by their thickness.

Table 3.6. Calibrated parameters for surface water features.

Parameter	Description	Calibrated Estimate	Unit
<i>SL1</i>	Streambed vertical leakance in Zone 1	0.36	1/day
<i>SL2</i>	Streambed vertical leakance in Zone 2	1.10E-03	1/day
<i>SL3</i>	Streambed vertical leakance in Zone 3	0.60	1/day
<i>SL4</i>	Streambed vertical leakance in Zone 4	0.89	1/day
<i>SL5</i>	Streambed vertical leakance in Zone 5	0.44	1/day
<i>SL6</i>	Streambed vertical leakance in Zone 6	0.16	1/day
<i>SL7</i>	Streambed vertical leakance in Zone 7	2.93	1/day
<i>SL8</i>	Streambed vertical leakance in Zone 8	1.84	1/day
<i>SL9</i>	Streambed vertical leakance in Zone 9	0.39	1/day
<i>SL10</i>	Streambed vertical leakance in Zone 10	0.16	1/day
<i>SL11</i>	Streambed vertical leakance in Zone 11	0.41	1/day
<i>SL12</i>	Streambed vertical leakance in Zone 12	0.31	1/day
<i>SL13</i>	Streambed vertical leakance in Zone 13	8.00	1/day
<i>SL14</i>	Streambed vertical leakance in Zone 14	7.31E-04	1/day
<i>bot_depth</i>	Depth from streambed surface to the bottom of streambed	2.50	m

3.5.7.2. Bonny Reservoir

The Bonny Reservoir, situated on the South Fork Republican River in Yuma County, Colorado, is the only significant water body within the MODFLOW model domain (Figure 3.1b).

In response to the 1935 flood event in the Republican River Basin, the United States Bureau of Reclamation officially started the construction of the Bonny Dam and Reservoir in December 1948 and finished the project in May 1951. Initially, the authorized purpose for the Bonny Reservoir was flood control, irrigation, recreation, and fish and wildlife conservation. However, some later feasibility studies revealed that the Bonny Reservoir was not “economically feasible to support irrigation” (Bureau of Reclamation, 2018). Nowadays, the Bonny Reservoir only supplies irrigation water to a few parcels of land via the Hale Ditch, which predates the construction of the reservoir.

The amount of water stored in the reservoir had remained approximately within a range of 43 to 49 Mm³ until the early 2000’s (Bureau of Reclamation, 2019), when the State of Colorado began to gradually empty the reservoir pursuant to a 2002 settlement reached between the three states of Colorado, Kansas, and Nebraska regarding compliance with the Republican River Compact (Republican River Compact Administration, 2019). The reservoir was completely drained by 2012, and since then it has remained empty and has been operated as a pass-through system by keeping the dam gates open (Bureau of Reclamation, 2018).

The interaction between stored water in the reservoir and groundwater is simulated using MODFLOW’s River (RIV) Package (Harbaugh et al., 2000; Figure 3.4). The RIV cells are active from October 1950 through April 2012. In these cells, the specified head value for a given stress period corresponds to the average water table elevation in the reservoir during that period (Bureau of Reclamation, 2019). In addition, the elevation of the reservoir bed’s bottom is calculated by subtracting the reservoir bed’s thickness (5.64m) from its top elevation; both of these values were sourced from the Bureau of Reclamation (2018). The hydraulic conductance of the reservoir bed is determined through the calibration of its vertical leakance (Zone 14 in Figure 3.15 and Table

3.6). For stress periods with inactive RIV cells, the RIV cells encompassing the line of the South Fork Republican River are replaced with STR cells.

3.5.7.3. Drains

In the areas of bedrock outcrop, groundwater moves horizontally along the bedrock contact within the aquifer and reaches the land surface in the stream valleys, forming springs and water holes, such as the Genoa springs and the Jolly water holes at the western boundaries. This phenomenon is simulated by placing drain cells in such areas (Figure 3.4) and using the Drain (DRN) Package in MODFLOW (Harbaugh et al., 2000). In the DRN cells, the drain elevation is equal to the average land surface elevation at the location of the stream line and same as the STR cells, the drain conductance is determined through the calibration of streambed vertical leakance values in different zones (Figure 3.15 and Table 3.6).

3.6. Model Calibration

To calibrate the MODFLOW model, we employed the Parameter Estimation software suite (PEST; Doherty, 2018), which is a widely used software for parameter estimation and uncertainty analysis in the field of groundwater modeling. The simulation period was divided into a calibration period (i.e., spanning from the predevelopment period to April 30, 2010) and a testing period (i.e., spanning from May 1, 2010 to September 30, 2018). The testing period allows us to evaluate the model's ability to reproduce unseen observed data during the calibration process. In this study, a total of 49 parameters were adjusted during the calibration process to achieve a satisfactory match between simulated and measured data. Tables 3.2, 3.3, 3.5, and 3.6 list the final values of these parameters.

Two types of calibration targets are incorporated in this study, namely measured

groundwater heads and estimated stream baseflows. A total number of 28,651 measured groundwater level records from 2,398 wells constitute head targets (Figure 3.3a; see Section 3.4 for more information on the acquisition of these records). We use the Head-Observation (HOB) package in MODFLOW (Hill et al., 2000) to obtain simulated groundwater heads at the exact location of observation wells, rather than at the center of finite difference cells.

To estimate baseflow targets, we collected daily discharge data from seven stream gauges located in the study area using the NWIS (see Figure 3.15 for stream gauge locations). Next, we utilized the Baseflow Filter Program (Arnold et al., 1995; Arnold and Allen, 1999) to estimate daily baseflows at each stream gauge. To establish baseflow calibration targets for the predevelopment period, we computed the average daily baseflow at each stream gauge for years before 1956 (i.e., before significant groundwater development in the study area). For the rest of the calibration period, we calculated the monthly average baseflow in April and October at each stream gauge, representing high and low baseflow periods, respectively. This process resulted in 508 estimated stream baseflows used as calibration targets.

We determined the initial weights of the calibration targets through the measurement error-based weighting approach (Hill and Tiedeman, 2007). This approach involves assigning a weight to each target that is equal to the inverse of 1.96, which corresponds to the 95% confidence interval, multiplied by the expected uncertainty associated with the measurement error of the target. The expected uncertainty considered for head targets in the predevelopment period was 10 ft (3.05 m), while in the years following the predevelopment period, it was 5 ft (1.52 m; Peterson et al., 2016). For estimated stream baseflow targets, the expected uncertainty was assumed to be 10% of the average daily baseflow at each stream gauge (Peterson et al., 2016). Once we estimated the initial weights for calibration targets, we calculated the initial objective function and determined the total

contribution of head and baseflow targets. To balance the contribution of head and baseflow targets, we multiplied the initial weights assigned to baseflow targets by a constant factor, which was determined through trial and error. The resulting products were used as the final weights for baseflow targets. We did not modify the initial weights assigned to head targets.

To stabilize the parameter estimation process in this study, we employed two common types of regularization techniques used in groundwater modeling: Tikhonov regularization and Singular Value Decomposition (SVD). Tikhonov regularization involves constraining calibration parameters by adding soft knowledge (i.e., prior information) to the calibration process. Soft knowledge can include anything we know about the system before model calibration. This technique incorporates soft knowledge into the parameter estimation process by adding a soft knowledge deviation term to the objective function (Anderson et al., 2015; Doherty, 2018). By including this term in the objective function, the model is penalized for deviations from soft knowledge. SVD is a regularization technique used to achieve numerical stability in an ill-posed inverse problem by reducing the dimensionality of the Jacobian matrix (Anderson et al., 2015; Doherty, 2018). The size of the Jacobian matrix is reduced through creating linear combinations of parameters and including only identifiable parameter combinations in the parameter estimation process.

The parameter estimation process was carried out in two consecutive steps. In the first step, we only calibrated the parameters for the predevelopment period. Since a steady-state model is used to simulate this period, the aquifer storage parameters (i.e., S_y parameters) were omitted from the calibration process. To constrain the precipitation recharge parameters in this step, we acquired the values of average annual precipitation recharge in different recharge zones (excluding the alluvium zone) from the precipitation recharge maps provided in Peterson et al. (2016). These

values were then incorporated as soft knowledge into the calibration process by assuming they corresponded to annual precipitation recharge values computed using Equation 3.6 for an annual precipitation of 435 mm (i.e., the average annual precipitation between 1946 and 2018).

During the first step, we were able to adjust the parameters quickly, given significantly shorter execution time of the steady-state model. The calibrated values were then used as initial values in the second step. Additionally, the calibrated values for the aquifer conductivity parameters (i.e., K parameters) were incorporated as soft knowledge in the second step. In this step, we calibrated the parameters for the entire calibration period. As in the first step, we used average annual precipitation recharge values as soft knowledge. During the second step, we initially noticed that PEST tends to maximize all S_y parameters. Therefore, we constrained these parameters by determining their typical values based on the information available in previous works (Liu et al., 2010; McGuire et al., 2012; Peterson et al., 2016) and incorporating them as soft knowledge. To expedite the calibration process, we utilized Parallel PEST (Doherty, 2018), which allows for multiple model runs to be performed simultaneously across multiple processor cores and machines. This parallelization speeds up the construction of the Jacobian matrix by perturbing multiple parameters at the same time.

It is worth noting that while we have constructed a modified version of the MODFLOW model, namely the MODFLOW-RS model, we only calibrated the parameters for the MODFLOW model and incorporated the calibrated values into the MODFLOW-RS model as well.

3.7. Sensitivity Analysis

During each iteration of the parameter estimation process, PEST computes the composite sensitivity of each parameter and stores them in a parameter sensitivity file. The composite

sensitivity of a parameter refers to the magnitude of the corresponding column in the Jacobian matrix, normalized by the number of calibration targets. Each element in the column is multiplied by the weight assigned to the relevant calibration target (Doherty, 2018). Table 3.7 shows the composite sensitivity values, percentages, and rankings of the parameters. These were computed based on the calibrated parameter values, excluding the regularization features outlined in Section 3.6. These results provide valuable insights into the underlying structure of the MODFLOW model. The top 10 parameters with the highest composite sensitivity values are all from three categories of parameters, namely precipitation recharge, aquifer conductivity, and aquifer storage. This underscores the importance of the precipitation recharge and hydrogeological properties in the model's structure.

The aquifer conductivity and aquifer storage parameters that correspond mainly to the Ogallala Formation, which stores the primary portion of groundwater in the HPA, exhibit the highest sensitivity values among the various parameters in these categories. The top three parameters with the highest composite sensitivity values (in descending order) among the parameters in the surface water-groundwater interaction category are the streambed vertical leakance values for zones 6, 5, and 8, which correspond to the upstream tributaries of the South Fork Republican River, main stem of the Arikaree River, and main stem of the South Fork Republican River, respectively (Figure 3.15).

Table 3.7. Composite sensitivity values, percentages, and rankings of calibrated parameters.

Sensitivity Rank	Parameter	Category	Sensitivity	%
1	<i>b</i> _medium	Precipitation Recharge	2.08E-01	34.3
2	<i>b</i> _coarse	Precipitation Recharge	8.79E-02	14.5
3	<i>a</i> _medium	Precipitation Recharge	8.08E-02	13.3
4	<i>K</i> 7	Aquifer Conductivity	5.35E-02	8.8
5	<i>K</i> 6	Aquifer Conductivity	3.35E-02	5.5
6	<i>b</i> _fine	Precipitation Recharge	2.51E-02	4.1
7	<i>a</i> _coarse	Precipitation Recharge	2.13E-02	3.5
8	<i>Sy</i> 4	Aquifer Storage	1.67E-02	2.8
9	<i>Sy</i> 5	Aquifer Storage	1.43E-02	2.4
10	<i>K</i> 5	Aquifer Conductivity	1.04E-02	1.7
11	<i>SL</i> 6	Surface water-Groundwater Interaction	1.02E-02	1.7
12	<i>SL</i> 5	Surface water-Groundwater Interaction	8.43E-03	1.4
13	<i>a</i> _fine	Precipitation Recharge	7.27E-03	1.2
14	<i>Sy</i> 2	Aquifer Storage	7.24E-03	1.2
15	<i>SL</i> 8	Surface water-Groundwater Interaction	4.03E-03	0.7
16	<i>SL</i> 14	Surface water-Groundwater Interaction	1.80E-03	0.3
17	<i>Sy</i> 1	Aquifer Storage	1.78E-03	0.3
18	<i>SL</i> 3	Surface water-Groundwater Interaction	1.72E-03	0.3
19	east_bnd_before_1960	Boundary Flow	1.48E-03	0.2
20	<i>SL</i> 12	Surface water-Groundwater Interaction	1.27E-03	0.2
21	north_bnd_before_1960	Boundary Flow	1.15E-03	0.2
22	<i>SL</i> 10	Surface water-Groundwater Interaction	8.33E-04	0.1
23	north_bnd_after_1960_sp1	Boundary Flow	7.57E-04	0.1
24	<i>Sy</i> 3	Aquifer Storage	6.79E-04	0.1
25	east_bnd_after_1960_sp1	Boundary Flow	6.41E-04	0.1
26	<i>SL</i> 11	Surface water-Groundwater Interaction	5.59E-04	0.1
27	north_bnd_after_1960_sp2	Boundary Flow	5.51E-04	0.1
28	<i>SL</i> 7	Surface water-Groundwater Interaction	5.44E-04	0.1
29	south_bnd_before_1960	Boundary Flow	5.32E-04	0.1
30	<i>a</i> _alluvium	Precipitation Recharge	4.87E-04	0.1
31	east_bnd_after_1960_sp2	Boundary Flow	4.58E-04	0.1
32	south_bnd_after_1960_sp1	Boundary Flow	4.46E-04	0.1
33	enhncmnt_factor	Precipitation Recharge	4.34E-04	0.1
34	south_bnd_after_1960_sp2	Boundary Flow	2.96E-04	0.0
35	<i>K</i> 4	Aquifer Conductivity	2.77E-04	0.0
36	<i>SL</i> 13	Surface water-Groundwater Interaction	2.31E-04	0.0
37	<i>K</i> 1	Aquifer Conductivity	2.12E-04	0.0
38	<i>SL</i> 9	Surface water-Groundwater Interaction	2.03E-04	0.0
39	<i>b</i> _alluvium	Precipitation Recharge	1.95E-04	0.0
40	<i>SL</i> 2	Surface water-Groundwater Interaction	1.80E-04	0.0
41	<i>P</i> ₀ _medium	Precipitation Recharge	1.38E-04	0.0
42	<i>SL</i> 1	Surface water-Groundwater Interaction	1.35E-04	0.0
43	bot_depth	Surface water-Groundwater Interaction	8.97E-05	0.0
44	<i>K</i> 3	Aquifer Conductivity	4.98E-05	0.0
45	<i>P</i> ₀ _coarse	Precipitation Recharge	4.33E-05	0.0
46	<i>SL</i> 4	Surface water-Groundwater Interaction	4.03E-05	0.0
47	<i>K</i> 2	Aquifer Conductivity	3.78E-05	0.0
48	<i>P</i> ₀ _fine	Precipitation Recharge	1.02E-05	0.0
49	<i>P</i> ₀ _alluvium	Precipitation Recharge	3.42E-08	0.0

3.8. Model Performance Evaluation

For a visual assessment of the MODFLOW model's performance after calibration, we have generated the scatter plots of calibration targets versus simulated values (Figures 3.16a to 3.16c). The equal distribution of the points around the 1:1 line in Figures 3.16a and 3.16b suggests there is no significant bias in simulated groundwater levels in both the predevelopment and 1946-2010 periods. Figure 3.16c shows that the MODFLOW model performs well in reproducing stream baseflows overall, but there are some discrepancies in the extreme values. Specifically, the model underestimates extreme high values and overestimates extreme low values. The underestimation of extreme high values may be due to inaccuracies in the baseflow separation technique, which sometimes result in overestimating baseflow values after significant precipitation events. The overestimation of extreme low values is likely because the MODFLOW model is a groundwater model that cannot account for water loss in streams through processes such as evaporation or seepage into riverbanks.

While measured groundwater level changes were not included as calibration targets in this study, we have generated a plot of measured groundwater level changes versus simulated values for the calibration period (Figure 3.16d). To increase the signal-to-noise ratio, groundwater level changes were computed at a 5-year interval, as recommended by Liu et al. (2010). In Figure 3.16d, positive and negative values of groundwater level change indicate rise and decline in groundwater level, respectively. Figure 3.16d suggests that while the MODFLOW model is not calibrated for groundwater level changes, it generally performs well and without bias in reproducing changes in groundwater levels between -4 and 0 m, where most of the data exist. However, the model underestimates both extreme rises and declines in groundwater levels. This could be partly attributed to measurement errors as well as a simplified representation of the groundwater system

provided by the model, which is unable to capture the complex mechanisms that lead to extreme changes in groundwater levels.

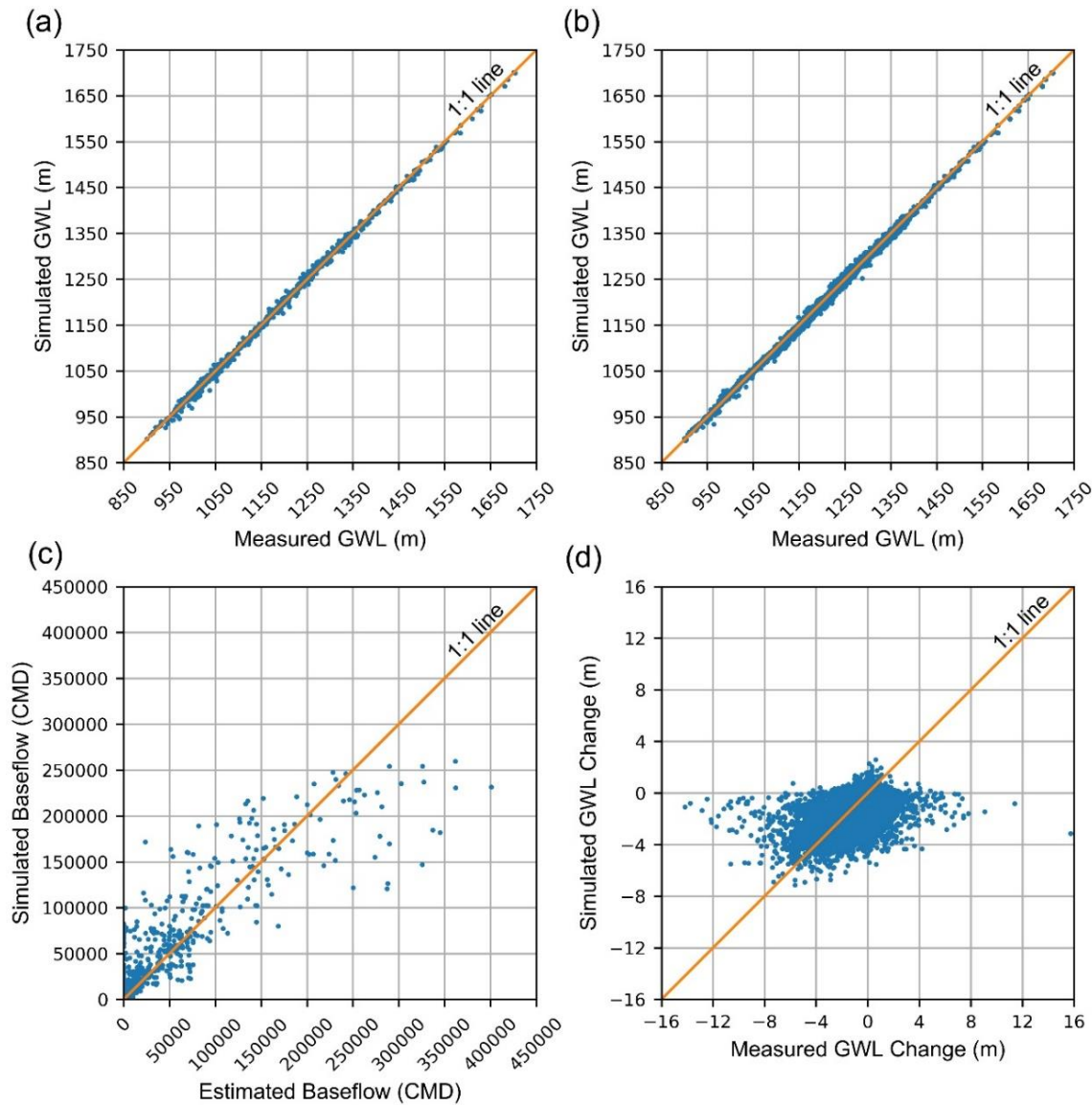


Figure 3.16. Scatter plots of measured (or estimated) values versus simulated values by the MODFLOW model during the calibration period. (a) Groundwater levels (GWLs) in the predevelopment period. (b) GWLs from 1946 to 2010. (c) Stream baseflows from 1946 to 2010. (d) GWL changes (computed at a 5-year interval) from 1946 to 2010.

The performance of the MODFLOW model declines in reproducing changes in groundwater levels between 0 and 4 m, as compared to the -4 to 0 m range (Figure 3.16d). This is

mainly due to the omission of occasional pauses in irrigated crop production at farmers' discretion (for reasons such as crop rotation, maintenance, etc.) in estimating groundwater withdrawals at irrigation wells for the MODFLOW model. Therefore, the MODFLOW model fails to simulate the rise in groundwater levels during these episodes of pumping cessation, underscoring the need for the MODFLOW-RS model. In the MODFLOW-RS model, groundwater withdrawals at irrigation wells during the 1984-2017 period were estimated using remotely sensed data of irrigated lands (Section 3.5.4.3).

The performance metrics of the MODFLOW and MODFLOW-RS models in reproducing groundwater levels during different simulation periods are presented in Table 3.8. The metrics demonstrate the superiority of the MODFLOW-RS model in reproducing groundwater levels. However, both models show a decline in performance during later simulation periods due to the propagation of errors from previous periods. Nevertheless, the rate of decline in performance either decreases or becomes reversed in the last two simulation periods, as shown by all metrics. The smaller rate of decline in performance during the 2010-2018 period, which was not included in the calibration process, compared to the 1980-1990 and 1990-2000 periods implies the robustness of both models in forecasting groundwater levels. Moreover, the ratio of mean absolute error (MAE) and root mean square error (RMSE) values to the range of measured groundwater levels throughout the simulation period are less than 1% for both models, indicating overall small errors and desirable model performance.

In order to further assess the performance of the MODFLOW and MODFLOW-RS models in reproducing groundwater levels, we have conducted a comparison with the Northern High Plains Aquifer MODFLOW model (Peterson et al., 2016), which is a highly parameterized model. The comparison reveals that the MODFLOW model performs similarly, while the MODFLOW-

RS model performs better in terms of MAE and RMSE. The values of bias, however, indicate that both the MODFLOW and MODFLOW-RS models have a tendency to underestimate groundwater levels in years after 1960 slightly, more so than the Northern High Plains Aquifer MODFLOW model. This discrepancy may be due to the overestimation of groundwater withdrawals at irrigation wells in the models constructed in this study.

Table 3.8. Models' performance metrics for groundwater levels and their changes.

Output Variable	Period	Number of Data	Model	Bias (m)	MAE (m)	RMSE (m)
Water Level	Predevelopment	982	MODFLOW	-0.03	4.27	6.03
Water Level	1946-1960	1,161	MODFLOW	-0.19	3.40	4.68
Water Level	1960-1970	4,062	MODFLOW	-0.86	3.67	4.83
Water Level	1970-1980	6,769	MODFLOW	-1.31	3.85	5.04
Water Level	1980-1990	4,976	MODFLOW	-2.90	4.79	6.01
			MODFLOW-RS	-2.49	4.52	5.73
Water Level	1990-2000	5,404	MODFLOW	-4.22	5.82	7.01
			MODFLOW-RS	-2.79	4.79	5.96
Water Level	2000-2010	5,297	MODFLOW	-4.05	5.91	7.21
			MODFLOW-RS	-2.38	4.73	6.05
Water Level	2010-2018	4,450	MODFLOW	-4.20	6.15	7.82
			MODFLOW-RS	-2.39	4.96	6.57
Water Level Change (5-yr interval)	1984-2018	16,635	MODFLOW	-0.31	0.94	1.48
			MODFLOW-RS	-0.05	0.81	1.37

Note: Saturated thickness at measurement points during the predevelopment period varies from 0.5 to 91 m, with an average of 33 m. Measured groundwater levels from predevelopment to 2018 range from 900 to 1704 m.

Performance metrics of the MODFLOW and MODFLOW-RS models in reproducing changes in groundwater levels during the 1984-2018 period are also presented in Table 3.8. The metrics suggest that the MODFLOW-RS model outperforms the MODFLOW model. In addition, we have compared these metrics with similar ones computed for the Southwest Kansas MODFLOW model (Liu et al., 2010). The comparison indicates that both the MODFLOW and

MODFLOW-RS models outperform the Southwest Kansas MODFLOW model in terms of all three metrics. It should be noted that unlike the models developed in this study, changes in groundwater levels were incorporated as calibration targets for the Southwest Kansas MODFLOW model. Despite this advantage, our models still outperform the Southwest Kansas MODFLOW model, highlighting their superior performance.

Table 3.9 displays the performance metrics of the MODFLOW and MODFLOW-RS models in estimating average stream baseflows during April and October at every stream gauge (see Figure 3.1b for stream gauge locations). The metrics demonstrate that the MODFLOW model slightly outperforms the MODFLOW-RS model, taking into account that we have only calibrated the parameters for the MODFLOW model. The Kling-Gupta Efficiency (KGE; Gupta et al., 2009) is greater than or slightly less than 0.5 for most stream gauges and greater than or equal to 0.24 for the rest. According to Knoben et al. (2019), a KGE value greater than -0.4 indicates significantly better performance than the mean values. Therefore, both models exhibit satisfactory performance based on the KGE values. In addition, the RMSE values are reasonably small for both models, as the ratio of RMSE to the estimated baseflow range is less than or equal to 20% for all gauges except gauge A. According to Moriasi et al. (2015), both models have either a very good or good performance in terms of percent bias (PBIAS) in all gauges except gauges E and F. While the PBIAS values indicate that both models tend to overestimate baseflows at all gauges except for gauge B in the case of the MODFLOW model, we deem the models' performance adequate. This is because these models are not surface water models and therefore do not account for water loss in streams due to processes such as evaporation or seepage into riverbanks.

Table 3.9. Models' performance metrics for average stream baseflows in April and October.

Stream Gauge	Period of Data	Number of Data	Min Estimated Baseflow* (CMD)	Max Estimated Baseflow* (CMD)	Model	PBIAS	RMSE (CMD)	KGE
Gauge A (USGS 06822000)	1951-1964	16	43,412	58,810	MODFLOW	5.44%	4,739	0.24
Gauge B (USGS 06821500)	1946-2018	144	0	75,730	MODFLOW	-0.41%	13,970	0.48
					MODFLOW-RS	6.46%	14,125	0.44
Gauge C (USGS 06825000)	1950-1971	42	1,920	93,689	MODFLOW	0.04%	17,054	0.29
Gauge D (USGS 06825500)	1950-1976	52	148	7,200	MODFLOW	2.89%	1,433	0.48
Gauge E (USGS 06827000)	1946-1956 & 2002-2018	52	406	168,563	MODFLOW	15.46%	22,922	0.68
					MODFLOW-RS	21.15%	23,279	0.63
Gauge F (USGS 06827500)	1946-2018	144	0	325,565	MODFLOW	34.10%	49,033	0.44
					MODFLOW-RS	41.45%	50,273	0.37
Gauge G (USGS 06824500)	1947-1995 & 2014-2018	105	11,750	400,919	MODFLOW	3.38%	56,854	0.56
					MODFLOW-RS	4.87%	56,905	0.54

* April and October averages estimated based on measured daily streamflow data. CMD stands for cubic meters per day.

As with groundwater levels, we have compared the performance of the MODFLOW and MODFLOW-RS models in estimating April and October baseflows with the Northern High Plains Aquifer MODFLOW model (Peterson et al., 2016). The performance metrics considered by Peterson et al. (2016) indicate that both the MODFLOW and MODFLOW-RS models perform better than the Northern High Plains Aquifer MODFLOW model at stream gauges B (USGS 06821500) and F (USGS 06827500). However, the Northern High Plains Aquifer MODFLOW model outperforms both models at stream gauge G (USGS 06824500).

Figures 3.17a and 3.18a display hydrographs of measured and simulated groundwater levels at eight wells across the study area for the MODFLOW and MODFLOW-RS models, respectively. Additionally, we have generated hydrographs of estimated and simulated April and

October baseflows at all stream gauges for both models (Figures 3.17b and 3.18b). See Figure 3.1b to locate the wells and stream gauges. Furthermore, Figure 3.17b displays the estimated and simulated baseflows at every stream gauge during the predevelopment period. The vertical dotted lines in Figure 3.18 separate years before 1984, as the models are identical before that year.

Figures 3.17 and 3.18 show that both models reasonably reproduce the general temporal trends with R-values greater than 0.7 for most wells and gauges. However, a comparison of Figures 3.17a and 3.18a demonstrates the higher accuracy of the MODFLOW-RS model in computing groundwater levels, particularly in wells 2, 4, 5, 6, and 7. These wells share a common feature in their measured groundwater level hydrographs, which is a decreasing trend in decline rates from the mid-1980's to the mid-1990's. Remote sensing data indicates that this flattening trend is attributed to a temporal pause of irrigation in many irrigated parcels in Kit Carson County, Colorado, as well as Cheyenne and Sherman counties in Kansas. Agricultural Census data (U.S. Department of Agriculture, 2019c) also show a decrease in the total area of irrigated lands in these three counties during the census years of 1982, 1987, and 1992. While the reason is uncertain, it could possibly be due to a transition from flood to center pivot irrigation systems. This period of irrigation cessation highlights the advantages of using remote sensing data in the estimation of groundwater withdrawals at irrigation wells.

Based on the model performance evaluations and comparisons in this section, it can be concluded that both the MODFLOW and MODFLOW-RS models exhibit desirable performance, taking into account their regional, single-layer, and sparsely parameterized nature. The MODFLOW model has been designed to allow for complete control over groundwater diversion and recharge at every irrigation well and pertinent irrigated parcel, making it highly adaptable for integration into a hydro-economic modeling framework that includes field scale (parcel scale)

agronomic and economic models.

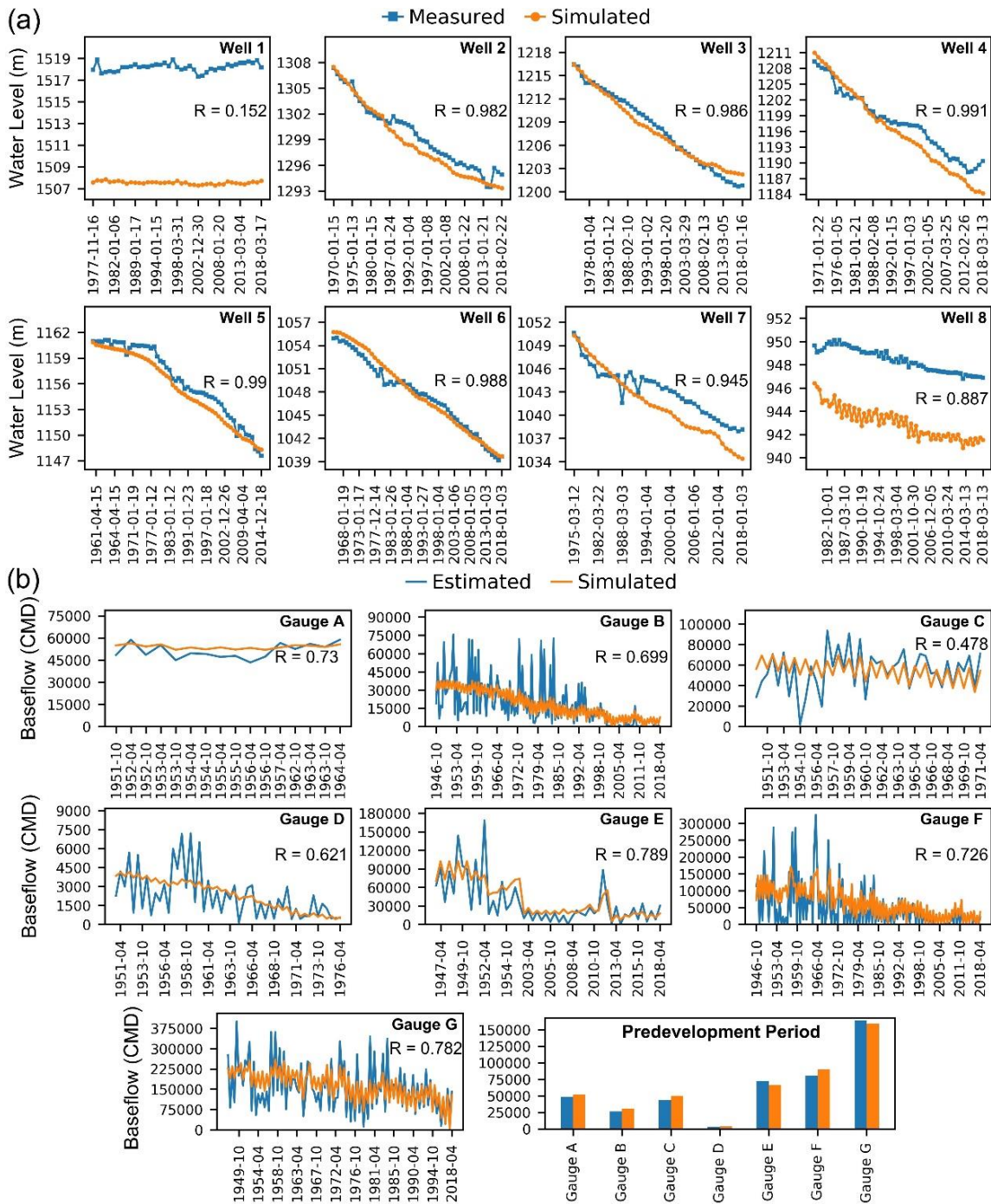


Figure 3.17. Hydrographs for various wells and stream gauges, comparing measured (or estimated) data with simulated values from the MODFLOW model. (a) Groundwater levels. (b) Average baseflows for April and October. The bar chart displays the estimated versus simulated baseflows in every stream gauge during the predevelopment period. CMD stands for cubic meters per day.

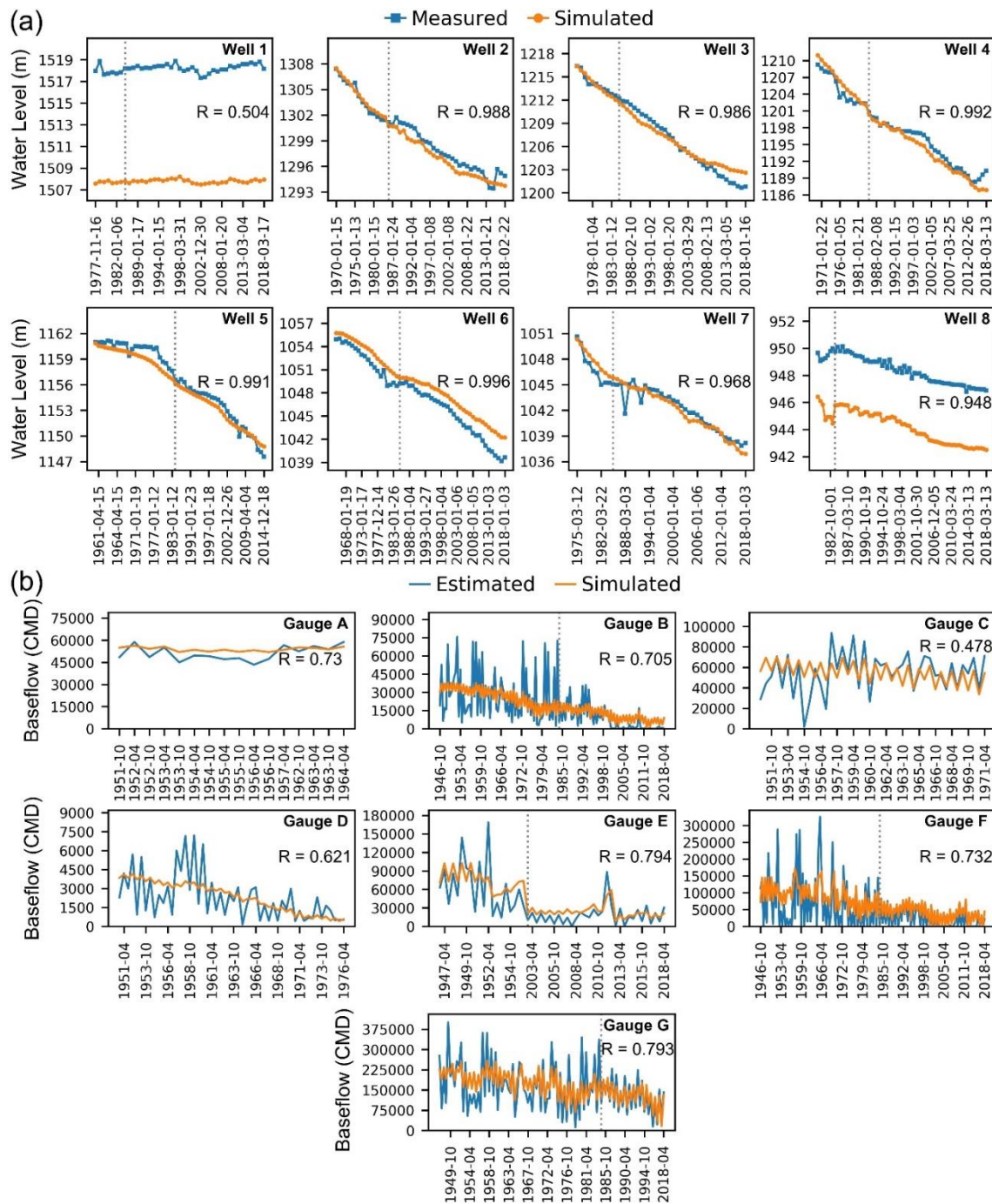


Figure 3.18. Hydrographs for various wells and stream gauges, comparing measured (or estimated) data with simulated values from the MODFLOW-RS model. Vertical dotted lines separate data before 1984, as results are generated by the MODFLOW model prior to this year. (a) Groundwater levels. (b) Average baseflows for April and October. CMD stands for cubic meters per day.

CHAPTER 4.

CAPTURING HUMAN-CROP-GROUNDWATER INTERACTIONS: MODELING REAL-
WORLD AGENTS IN AN INTENSIVELY IRRIGATED REGION OF THE U.S. HIGH
PLAINS ²

Highlights

Global food security faces threats due to the rapid depletion of crucial aquifers in arid and semi-arid regions worldwide. Addressing this challenge requires effective groundwater management policies that prolong aquifer lifespan while minimizing costs to farmers. Hydro-economic models serve as cutting-edge tools for shaping these policies, but their reliability is typically compromised by oversimplifications. In this study, we develop an agent-based hydro-economic model (ABM-MODFLOW) for a portion of the High Plains Aquifer in the U.S., aiming to overcome the limitations observed in existing models. Through interdisciplinary collaboration, each component of our model was specifically designed to align with our research objectives. We simulate planting and irrigation decisions using a detailed representation of real-world farmers. Additionally, well capacity is incorporated as a constraint on irrigation duration. A unique aspect of our study is the rigorous validation of the hydro-economic model to establish its credibility. The validation results indicate satisfactory performance in reproducing historical data and trends. They also reveal the superiority of the hydro-economic model over the standalone groundwater model in simulating the groundwater system. Furthermore, the model outcomes accentuate the influence of soil type on agents' profitability, particularly for those with limited irrigation capacities.

² This chapter has been submitted for publication in Water Resources Research as a journal article titled "Capturing human-crop-groundwater interactions: Modeling real-world agents in an intensively irrigated region of the U.S. High Plains" and is currently under review.

Overall, the highest profits are earned by agents with high irrigation capacities and fine soils, while the lowest are achieved by those with low irrigation capacities and coarse soils. The ABM-MODFLOW model offers an advanced approach to simulate interactions among human decisions, crops, and groundwater, aiding in the formulation of effective groundwater management policies.

4.1. Introduction

Global food production heavily relies on a number of large and highly stressed aquifers, such as the Upper Ganges in India, the High Plains in the United States, and the North China Plain in China (Famiglietti, 2014; Gleeson et al., 2012b; Taylor et al., 2013). The rapid depletion of groundwater in these aquifers has placed irrigated crop production and consequently global food security in jeopardy (Aeschbach-Hertig and Gleeson, 2012; Famiglietti, 2014; Scanlon et al., 2012).

Groundwater depletion in intensively irrigated regions arises from the imbalance between groundwater recharge and extraction, making it essential to address this issue within a hydrologic framework. However, given that human activities are the main cause of this imbalance and rural communities heavily rely on irrigated agriculture as a valuable source of income (Lauer et al., 2018), it is impractical to devise solutions without considering the economic factors.

From an economic standpoint, groundwater depletion is rooted in the common-pool nature of groundwater resources and the associated tragedy of the commons, wherein individual users have no incentive to restrict their extraction to a level that is socially optimal (Aeschbach-Hertig & Gleeson, 2012; Rouhi Rad et al., 2020a; Steward et al., 2013). Addressing groundwater depletion within this context often necessitates implementing a range of policy instruments that

extend the lifespan of the aquifer, while minimizing the economic costs associated with reduced water use (Hrozencik et al., 2017).

Hydro-economic models, which integrate neoclassical economics with hydrology, are state-of-the-art tools for the investigation and formulation of water management policies (Harou et al., 2009; Kahil et al., 2016). Over the past four decades, extensive research has utilized hydro-economic modeling to assess the costs and benefits of groundwater management policies (Aistrup et al., 2017; Brill and Burness, 1994; Gisser and Sánchez, 1980). However, previous studies have often undervalued the significance of using relevant groundwater models, which serve as the foundation of hydro-economic models. Following the findings of Brozović et al. (2010) regarding the underestimation of pumping externalities when employing a lumped groundwater model with infinite hydraulic conductivity (commonly referred to as a “bathtub” model), several studies incorporated spatially distributed groundwater models into their hydro-economic models.

Guilfoos et al. (2013) developed a custom-made groundwater model in which groundwater flow is simulated using Darcy’s Law. Despite explicitly modeling groundwater flow, the model exhibits various oversimplifications, such as assuming spatially uniform and temporally constant precipitation recharge, hydraulic conductivity, specific yield, and flow cross-sectional area across all model cells. These simplifications could negatively affect the reliability of the hydro-economic model outputs. While Guilfoos et al. (2016) managed to address some of these limitations, certain constraints still persist. These include considering a constant specific yield for all model cells, assuming temporally constant precipitation recharge, and incorporating unrealistic boundary conditions.

Several other studies have utilized pre-existing regional MODFLOW models (Harbaugh et al., 2000), originally developed for purposes other than hydro-economic modeling (Hrozencik et

al., 2017; Hu et al., 2015; Khan & Brown, 2019; Mulligan et al., 2014; Noël & Cai, 2017; Rouhi Rad et al., 2020b). While leveraging pre-existing groundwater models greatly facilitates the development of hydro-economic models, it is important to note that these models have limitations in terms of providing full control over various aspects, particularly groundwater recharge. Specifically, all of these studies fail to consider the impact of variations in irrigated area on precipitation recharge, despite the fact that irrigation enhances precipitation recharge by increasing soil moisture (Cherry et al., 2020). A previous modeling study in a semi-arid area has estimated that annual precipitation recharge in irrigated lands is increased by a factor of 2.0 (Liu et al., 2010). Allowing control over different components of the groundwater budget, such as recharge, is critical because future simulations or policy analyses using hydro-economic models may involve land use changes, which can affect groundwater recharge.

Additionally, some of these studies do not incorporate the computation of irrigation return recharge based on irrigation amounts, instead relying on initially specified values in the models (Hrozencik et al., 2017; Hu et al., 2015; Rouhi Rad et al., 2020b). Previous modeling studies in semi-arid regions have shown that up to 25% of total pumped water for irrigation could return to the saturated zone as recharge, depending on the irrigation system (Liu et al., 2010; Republican River Compact Administration, 2003). The overestimation (underestimation) of groundwater recharge would subsequently lead to the underestimation (overestimation) of groundwater depletion costs.

In addition to the hydrologic component, the reliability and applicability of hydro-economic models is heavily dependent on the accurate representation of water users. In a hydro-economic model, when decision-making units represent individual water users rather than a central planner, the economic component can be classified as an agent-based model (ABM). In regions

where groundwater-fed irrigation is prevalent, agents are the farmers who utilize groundwater for irrigated crop production. These agents make decisions on the entirety of their farm, based on specific characteristics of their irrigation well(s), such as well capacity, as well as the attributes of the parcel(s) in their farm, including parcel size and soil type. Notably, existing research has highlighted that farm size plays a crucial role in shaping the planting and irrigation decisions made by each agent (Saak and Peterson, 2012).

Previous studies, however, have overlooked the inclusion of agents that represent real-world farmers. Many studies have created agents by clustering individual irrigation wells using model reduction techniques (Khan and Brown, 2019; Mulligan et al., 2014), aggregating individual wells that reside within the same groundwater model cell (Guilfoos et al., 2016, 2013; Noël and Cai, 2017), or defining them based on political or regulatory boundaries (Aistrup et al., 2017; Hu et al., 2015; Lei et al., 2019). In other cases, agents are represented by individual irrigation wells with a uniform parcel size (Hrozencik et al., 2017; Rouhi Rad et al., 2020b). These approaches fail to capture the significant heterogeneity that exists among agents at the regional scale and can miscalculate the path and the costs of groundwater depletion.

Agents' decisions in hydro-economic models are also significantly influenced by decreased well capacity, which has been identified as a major concern by groundwater management organizations (Hrozencik et al., 2023). Declining well capacity imposes constraints on irrigation application rates, leading to significant reductions in irrigated area, total seasonal water use, and profits (Foster et al., 2014). The decline in well capacity extends the time interval between consecutive irrigation applications, resulting in prolonged periods without irrigation. Failing to explicitly account for this constraint associated with the duration of irrigation applications can lead to unreliable predictions of groundwater use, crop yield, and profitability (Domínguez et al., 2022).

Nevertheless, the impact of well capacity on irrigation duration has received limited attention in previous hydro-economic modeling studies.

Within hydro-economic models, the agronomic component plays a crucial role in simulating agents' decisions by generating crop-water production functions that establish the relationship between water use and crop yield. While the importance of incorporating crop simulation models as advanced tools for constructing stochastic crop-water production functions has been acknowledged in recent studies (Foster et al., 2014; Hrozencik et al., 2017), only one study to date has utilized these models' outputs to simulate both preseason planting and irrigation decisions of farmers within a stochastic framework, considering uncertainties in weather conditions during the growing season (Rouhi Rad et al., 2020b).

In addition to the factors mentioned earlier that significantly influence the performance of hydro-economic models, conducting a comprehensive evaluation of their performance is essential yet challenging, as with other integrated models (Haacker et al., 2019; Voinov and Shugart, 2013). The credibility and acceptance of hydro-economic models among stakeholders heavily depend on their ability to sufficiently reproduce historical data (Harou et al., 2009). Employing hydro-economic models for policy analysis without robust performance evaluation raises doubt about the reliability of the findings and policy implications. However, previous hydro-economic models for groundwater systems have not undergone rigorous evaluation regarding their ability to reproduce observed data. While a few of these models have been partially tested (Aistrup et al., 2017; Guilfoos et al., 2016; Mulligan et al., 2014; Noël and Cai, 2017), their testing efforts were not comprehensive.

In this study, we present the development of a spatiotemporally explicit hydro-economic model for an intensively groundwater-fed irrigated region located in eastern Colorado and

northwest Kansas within the U.S. High Plains. Our primary objective is to address the aforementioned limitations identified in previous hydro-economic modeling studies. The hydro-economic model we develop comprises three key components: an agronomic model that simulates the biophysical processes governing crop growth and development, a spatially distributed groundwater model that provides complete control over groundwater diversion and recharge at every irrigation well and pertinent irrigated parcel, and an economic model that explicitly models irrigation and planting decisions of individual agents within a stochastic framework, based on the outputs of the agronomic model.

This study makes several significant contributions to the literature on hydro-economic modeling of groundwater systems. Firstly, we construct all the modeling components specifically for this study, with the explicit aim of integrating them into a hydro-economic modeling framework. As such, our approach embodies the principles of integrated modeling, emphasizing close collaboration and interdisciplinary teamwork among specialists in various modeling methods and tools (Arnold, 2013). Secondly, the decision-making units in the economic model closely represent real-world agents in the study area, making it more applicable and realistic. Thirdly, our economic model takes into account well capacity and its effect on the duration of irrigation applications as a significant factor affecting farmers' decisions regarding planting and irrigation. Lastly, we undertake a comprehensive evaluation of our model's performance by comparing its outputs with different categories of observed data. These categories include water withdrawals from irrigation wells, groundwater levels, stream baseflows, crop yields, and farmers' planting decisions. This comparison provides a holistic assessment of the model's reliability.

The comprehensive validation of our model not only establishes its credibility but also highlights the suitability of our methodology for modeling heavily stressed groundwater systems

in arid and semi-arid regions affected by human activities. While specific groundwater management policies are not analyzed in this study, the exploration of the coevolution and dynamics of components within a coupled human-natural system provides valuable insights and policy implications for enhancing groundwater management in intensively groundwater-fed irrigated regions worldwide.

4.2. Materials and Methods

In this section, we first introduce the spatial domain of the hydro-economic model developed in this study and provide background information about the study area. We then describe the three key components of the hydro-economic model: the agronomic model, the economic model, and the hydrologic model. We demonstrate how our methodology addresses the limitations of previous hydro-economic models discussed earlier. Finally, we provide a description of our hydro-economic modeling framework, wherein the three model components are integrated to capture the dynamic interplay between farmers' activities and the groundwater system.

4.2.1. Study Area

The High Plains Aquifer (HPA), also known as the Ogallala Aquifer, is a vital water source for irrigated crop production in the High Plains region of the U.S. (Figure 4.1a). It has experienced the highest average groundwater depletion rate among major aquifer systems in the country since 1900, reaching 10.2 km³/yr during the 2001-2008 period (Konikow, 2015). Our hydro-economic model focuses on a domain within the HPA, covering 20,928 km² in the semi-arid western region of the Northern High Plains. This area incorporates portions of the Republican River and Smoky Hill River basins in eastern Colorado and northwest Kansas (Figure 4.1a).

The model domain covers 220,074 ha of irrigated lands, with 99.6% relying on groundwater diverted from the HPA through 4,038 irrigation wells (Figure 4.1b). Corn and winter wheat are the dominant crops in the study area, accounting for an average of 62% and 16% of the total irrigated area, respectively. During the 1946-2018 period, the average annual precipitation across the model domain was 435 mm, while the average seasonal net irrigation requirement was 385 mm for corn and 295 mm for winter wheat. However, meeting these high irrigation demands has resulted in significant declines in groundwater levels. Between 1999 and 2018, approximately 30% of the region experienced a 23% or more decline in saturated thickness.

Groundwater serves as the primary source of streamflow in the study area, playing a crucial role in maintaining water supply for aquatic ecosystems (Zipper et al., 2021). The widespread adoption of center pivot irrigation systems in the 1970's led to increased groundwater extraction, causing significant reductions in streamflow and triggering legal conflicts among Colorado, Kansas, and Nebraska. For more detailed information on the study area, including geological characteristics, administrative units, and the history of groundwater development, see Sections 3.2, 3.3, and 3.5.4.2 of Chapter 3.

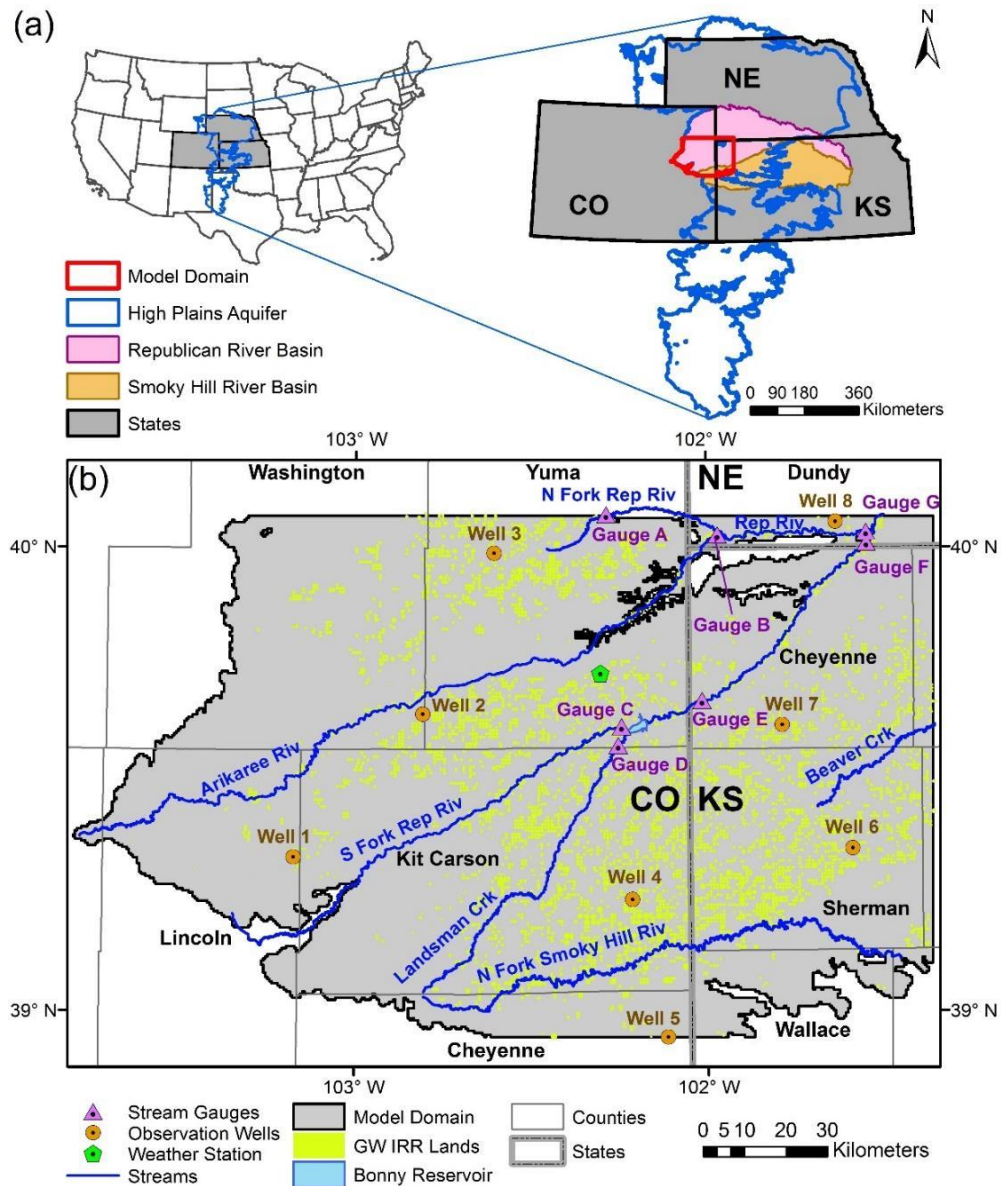


Figure 4.1. (a) Location of the hydro-economic model domain relative to the High Plains Aquifer and major river basins. (b) Map of the hydro-economic model domain and groundwater-fed irrigated (GW IRR) parcels.

4.2.2. Agronomic Model

In this study, we utilize the Decision Support System for Agro-Technology Transfer (DSSAT; Hoogenboom et al., 2019; Jones et al., 2003) to simulate crop yield, actual crop evapotranspiration (ET), and irrigation requirement under various soil, irrigation management, and

climate conditions. DSSAT is a comprehensive software package that incorporates 42 crop simulation models. These biophysical models are designed to simulate crop growth, development and yield while accounting for the interactions of crop genotype with its environment and management practices. DSSAT allows for the evaluation of different management strategies, including irrigation scheduling, fertilizer application, planting date, and crop rotations on a representative hectare of land. In addition to its wide usage for the evaluation of agricultural management practices (Thorp et al., 2008), DSSAT has been employed to estimate irrigation requirements for both data-driven and physically-based groundwater models (Sahoo et al., 2017; Xiang et al., 2020). However, its incorporation within hydro-economic models has been limited (Rouhi Rad et al., 2020b).

In this study, we employ the CERES-Maize and CERES-Wheat models of DSSAT version 4.7.5 to simulate the growth, development and yield of dryland and irrigated corn (*Zea mays* L.) and winter wheat (*Triticum aestivum* L.) in the study area from 1981 to 2019. The simulation models in DSSAT require several inputs, including climate data, cultivar coefficients, soil properties, and management practices.

For climate data, we utilize daily measurements of maximum temperature, minimum temperature, relative humidity, solar radiation, and wind speed from a weather station located in Idalia, Colorado (Figure 4.1b). These data are obtained from the Colorado Agricultural Meteorological Network (CoAgMET, 2019). Additionally, we use the gridded estimates of daily precipitation provided by PRISM Climate Group (2019) to capture precipitation data at the weather station's location. We choose to use PRISM precipitation data to maintain consistency with the groundwater model, as precipitation recharge is estimated using PRISM precipitation data (Section 3.5.6.1 in chapter 3). Furthermore, we incorporate the annual mean atmospheric carbon dioxide

concentrations measured at the Mauna Loa Observatory in Hawaii (Global Monitoring Laboratory, 2019) as an important climate input for DSSAT. As atmospheric carbon dioxide concentrations continue to rise due to greenhouse gas emissions, crop water productivity is expected to be enhanced, which could potentially lead to increased crop yields and reduced water use (Deryng et al., 2016). Previous hydro-economic modeling studies for groundwater systems have not included this parameter.

Calibrated cultivar coefficients for corn and winter wheat are obtained from two studies that estimated these coefficients using experimental field data collected at farms located in Fort Collins and Greeley, Colorado (DeJonge et al., 2011; Elsayed et al., 2019). These farms have climate conditions similar to our study area. The calibrated cultivar coefficients are listed in Table B1 of the Appendix B.

To simulate crop growth for various soil types, we identify the 15 prevalent soil types found in the groundwater-fed irrigated parcels within the study area. The physical properties of these soil types are obtained from the Soil Survey Geographic Database (SSURGO; Natural Resources Conservation Service, 2019). Table 4.1 offers a detailed overview of the 15 soil types, highlighting their distribution within the groundwater-fed irrigated parcels and their associated properties. The table indicates that silt loam collectively is the most widespread soil type, covering 67% of the groundwater-fed irrigated lands.

Developing irrigation management strategies in DSSAT involves specifying values for various parameters that influence the irrigation amount, timing, and duration. These parameters include irrigation efficiency, irrigation application depth, irrigation management depth, critical plant available water (PAW_c), and irrigation frequency (IFREQ). Table B2 in the Appendix B lists the values of these parameters. In this study, we execute DSSAT simulations for irrigated crops

using a combination of 6 distinct PAW_c and 24 IFREQ values, while keeping the remaining parameters constant.

Table 4.1. Prevalent soil types in groundwater-fed irrigated parcels and their properties

Soil Name	Soil ID	Land Coverage (%) [*]	Depth (cm)	WP (cm/cm) ^{**}	FC (cm/cm) ^{**}	SWC (cm/cm) ^{**}	AWC (cm/cm) ^{**}	Ksat (cm/hr) ^{**}	BD (g/cm ³) ^{**}
Haxtun Sandy Loam	1	4.2	201	0.18	0.32	0.44	0.14	2.18	1.51
Julesburg Loamy Sand	2	3.3	152	0.13	0.26	0.40	0.13	14.32	1.25
Valent Sand	3	5.6	203	0.06	0.11	0.36	0.05	60.21	1.43
Ascalon Sandy Loam	4	3.5	203	0.14	0.23	0.40	0.09	4.85	1.25
Colby Silt Loam	5	2.8	152	0.16	0.33	0.50	0.17	3.30	1.39
Haxtun Loamy Sand	6	4.4	201	0.19	0.33	0.44	0.14	1.93	1.63
Kuma Keith Silt Loam	7	17.2	155	0.20	0.39	0.50	0.19	3.60	1.29
Norka Silt Loam	8	14.6	170	0.19	0.37	0.50	0.18	3.30	1.24
Richfield Clay Loam	9	2.5	201	0.20	0.38	0.50	0.18	0.81	1.38
Satanta Loam	10	6.3	152	0.18	0.34	0.47	0.16	3.30	1.23
Keith Silt Loam	11	18.8	201	0.17	0.36	0.48	0.19	2.28	1.23
Ulysses Silt Loam	12	6.6	201	0.17	0.35	0.50	0.18	3.30	1.25
Bridgeport Silt Loam	13	1.0	152	0.17	0.36	0.44	0.19	3.30	1.33
Kuma Silt Loam	14	6.0	201	0.21	0.45	0.49	0.24	1.63	1.51
Manter Sandy Loam	15	3.2	152	0.11	0.22	0.43	0.11	10.16	1.41

* Percentage of the total area of groundwater-fed irrigated parcels

** Weighted average over 1 m depth based on the thickness of soil layers

WP, wilting point; FC, field capacity; SWC, saturation water content; AWC, available water capacity; Ksat, saturated hydraulic conductivity; BD, bulk density. Source of data is SSURGO (Natural Resources Conservation Service, 2021).

PAW_c establishes the soil moisture target and determines the timing of irrigation events. It is expressed as a percentage of the available water capacity (AWC), indicating the threshold at which irrigation is triggered when the plant available water (PAW) falls below this value. AWC

represents the maximum amount of water that the soil can hold for plant uptake, while PAW refers to the actual amount of water readily available to plants in the soil. Increasing PAW_c leads to more frequent trigger of irrigation events, greater crop water usage, and potentially higher crop yields. However, a new irrigation event can only start when the entire irrigated area has been irrigated during the previous event. The role of irrigation application duration is quantified by a variable named IFREQ (Kisekka et al., 2018), which sets the minimum time interval between the start of two consecutive irrigation events. This is equivalent to the minimum time required to irrigate the entire irrigated area during each event. It is calculated as follows:

$$IFREQ = \frac{\text{Irrigated Area} \times \text{Irrigation Application Depth}}{\text{Well Capacity}} \quad (4.1)$$

Given the constant irrigation application depth in this study (equal to 25 mm), IFREQ is determined by the size of the irrigated area and well capacity value. Well capacity is the maximum pumping rate that can be sustained throughout a growing season without the well going dry. IFREQ serves as a connection between groundwater availability and irrigation scheduling. As the well capacity declines while keeping the irrigated area constant, IFREQ increases. This increase results in longer periods without irrigation, which can significantly affect crop yield and seasonal irrigation use.

Figure 4.2 illustrates the combined and non-linear influence of different PAW_c and IFREQ values on the yield and seasonal irrigation use of corn and winter wheat within the study area, highlighting the importance of explicitly simulating the biophysical processes driving crop growth and development. In this figure, crop yield and seasonal irrigation use are averaged across different soil types and weather conditions from 1981 to 2019. Additionally, Figures B1 and B2 in the Appendix B demonstrate how variations in PAW_c and IFREQ affect the yield and seasonal

irrigation use of corn and winter wheat, respectively, across the six generalized soil categories of clay loam, loam, loamy sand, sand, sandy loam, and silt loam. Notably, in sandy soils that have lower water-holding capacity, both corn and winter wheat yields, along with their irrigation use, show higher sensitivity to changes in PAW_c and IFREQ.

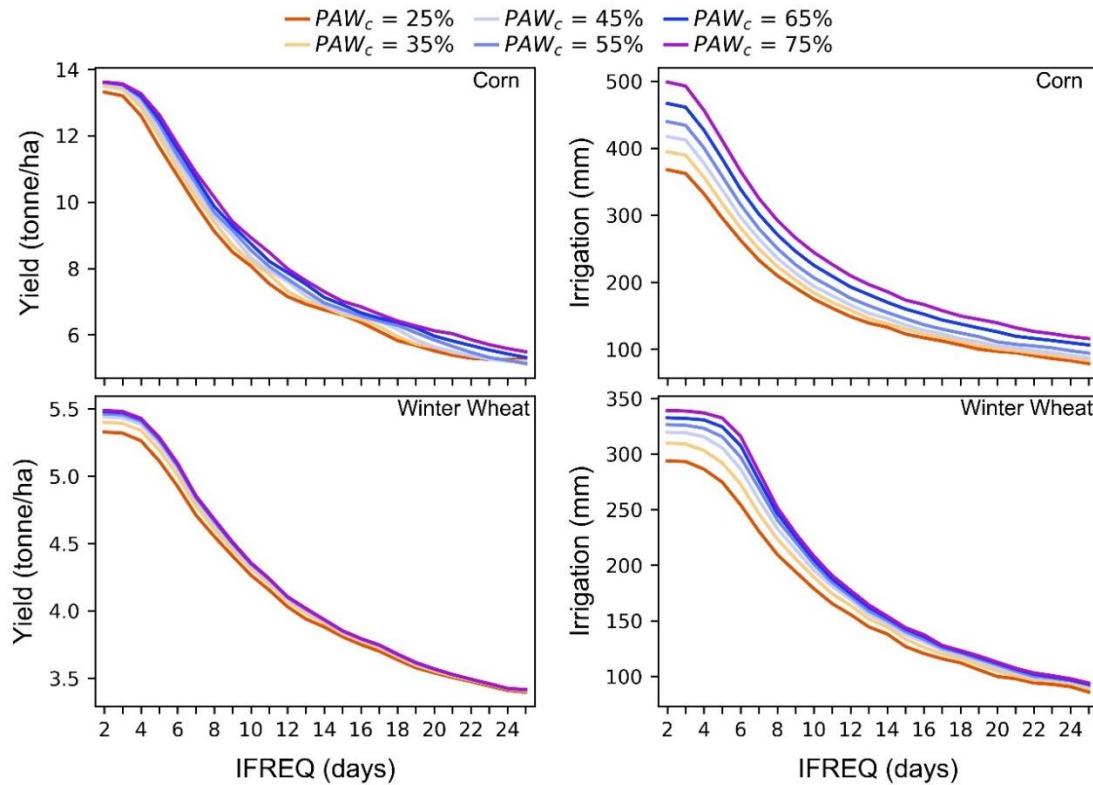


Figure 4.2. Yield and seasonal irrigation use of corn and winter wheat simulated by DSSAT for varying critical plant available water (PAW_c) and irrigation frequency (IFREQ) values. Data averaged across different soil types and weather conditions from 1981 to 2019. Note: 1 tonne/ha of corn is equal to 15.93 bu/ac, 1 tonne/ha of winter wheat to 14.87 bu/ac, and 1 mm to 0.039 in.

In terms of irrigation management parameters, the specified value of 85% for irrigation efficiency represents the typical value for the center pivot irrigation system (Irmak et al., 2011), which has been the dominant irrigation system in the study area since the early 1990's (Figure 3.12b in Chapter 3). For irrigated corn, irrigation is assumed to occur throughout its growing season, while for irrigated winter wheat, irrigation starts from spikelet initiation in spring following

winter dormancy. We disregard winter wheat irrigation applications in the previous fall, since fall irrigation using sprinkler systems is minimal in the study area (Rogers, 1997). For information on other management parameter values specified in DSSAT simulations, see Table B2 in Appendix B.

4.2.3. Economic Model

The initial step in developing the economic model is the creation of agents, as the model simulates the decision-making process of individual agents through a bottom-up approach.

In this study, we aim to create agents that represent their real-world counterparts and capture ground-level dynamics associated with these agents. To achieve this, we reviewed well permit and water right documents in the Colorado's Decision Support Systems (CDSS; Colorado Water Conservation Board & Colorado Division of Water Resources, 2019) and the Water Information Management and Analysis System (WIMAS; Kansas Geological Survey, 2019c). Using these resources, we identified all active and plugged irrigation wells in the study area and determined their places of irrigation, presented in the format of the Public Land Survey System (PLSS) quarter-quarter sections.

Having determined the places of irrigation for each well, we manually located and delineated all irrigated parcels, including both active and abandoned ones, throughout the study area. We located irrigated parcels using NAIP aerial imagery (U.S. Department of Agriculture, 2019a), the Landsat Legacy satellite images (Earth Resources Observation and Science (EROS) Center, 2019), and old aerial photographs (U.S. Geological Survey, 2019). Subsequently, we paired these parcels with their corresponding irrigation wells, defining each agent as a cluster of parcels and the associated irrigation wells used for their irrigation. Figure 4.3a illustrates the

heterogeneity among five different agents in the study area in terms of the number of irrigation wells and parcels within a small region.

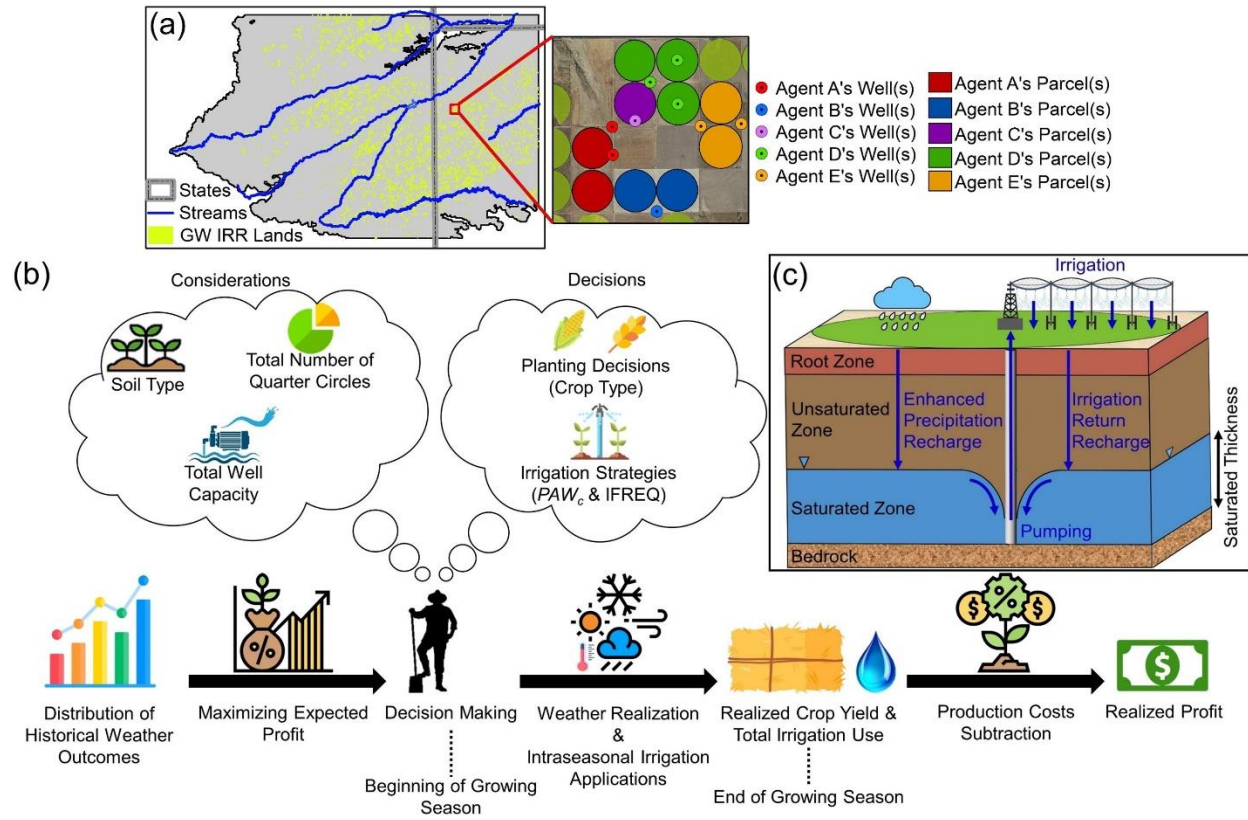


Figure 4.3. (a) Agents with varying numbers of irrigation wells and parcels. (b) The representation of the expected profit-maximizing agent's behavior in the economic model; PAW_c and IFREQ represent critical plant available water and irrigation frequency, respectively. (c) Feedbacks between agents' decisions and the groundwater system captured by the hydro-economic model.

Each agent's exclusive parcel and well properties are then derived from collected data along with existing datasets: the total farm area (determined by summing up parcel areas), the dominant soil type (sourced from the SSURGO database), and the total well capacity (computed by aggregating individual well capacities). Given the variability in total farm area and total well capacity among agents, a key attribute for comparing their profitability is the irrigation capacity, defined as:

$$\text{Irrigation Capacity} = \frac{\overline{Q}}{\overline{A}} \quad (4.2)$$

where $\overline{Q}$ represents the total well capacity and $\overline{A}$ denotes the total farm area for a given agent.

Well capacities are annually updated as discussed in Section 4.2.5. The spatial variation of weather conditions across the agents is not considered here, as DSSAT simulations are carried out using weather data obtained from a single weather station.

Following the determination of agents' attributes, we proceed with the development of the economic model. This model, implemented in the R programming language, represents profit-maximizing producers (agents) and aims to determine the optimal decisions for each agent. The model assumes that agents behave myopically, i.e., they maximize their net expected gains at the end of the upcoming growing season without considering potential increases in profitability in subsequent growing seasons. Although some agents may act strategically in reality, previous research in groundwater resource economics justifies the assumption of myopic behavior when all agents act myopically (Guilfoos et al., 2013; Koundouri, 2004).

In the economic model, agents' smallest farm management unit is a 13.15 ha (32.5 ac) plot of land, representing a quarter of the typical 52.61 ha (130 ac) circle found in the region. This size is chosen based on input from local farmers, who deem it as the minimum practical size for efficient crop and irrigation management (Hrozencik et al., 2017). Each agent possesses a specific number of these quarter circles, and their decisions are simulated for each individual unit. Within the economic model, agents make decisions pertaining to crop selection, choosing either irrigated corn, dryland corn, irrigated winter wheat, or dryland winter wheat. They also determine the PAW_c for irrigated crops. While agents do not explicitly choose IFREQ, their planting decisions

collectively determine the total irrigated area on their farms, which, in combination with the total well capacity, determines IFREQ (Equation (4.1)).

The decision-making process of agents follows a two-step approach (Figure 4.3b). In the first step, which marks the beginning of the growing season, agents determine both planting and irrigation strategies without having perfect foresight about upcoming weather conditions. Agents account for the uncertain nature of weather conditions by considering a distribution of historical weather outcomes (climate) from 1981 to 2019, assigning equal weight to each year. At the beginning of each growing season, a representative risk-neutral agent aims to maximize their expected annual profit by determining the total area planted in irrigated crop n along with the corresponding PAW_c value, as well as the total area planted in dryland crop m , according to the following equation:

$$\begin{aligned} \max E(\pi) = & \max_{A_n, PAW_{cn}, A_m} E_{weather} \left\{ \sum_{n=1}^N A_n [p_n f_n(w_n(PAW_{cn}, \text{IFREQ}(\bar{A} \right. \\ & - \sum_{m=1}^M A_m, \bar{Q}), \text{weather}), \text{weather}, \text{soil}) - w_n c - h_n] \\ & \left. + \sum_{m=1}^M A_m [p_m f_m(\text{weather}, \text{soil}) - h_m] \right\} \end{aligned} \quad (4.3)$$

where A_n and A_m are the total area planted in irrigated crop n and dryland crop m , respectively. This is calculated by multiplying the number of quarter circles planted with each crop by 13.15 ha (32.5 ac). PAW_{cn} denotes the selected PAW_c value for irrigated crop n . p_n and p_m represent the price of irrigated crop n and dryland crop m , respectively. The production function f_n generates the crop yield per unit land area for irrigated crop n based on the total irrigation applied per unit land area (w_n), seasonal weather realizations, and soil type. w_n is determined by

weather realization, PAW_{cn} , and IFREQ, where the latter itself depends on the total irrigated area and the total well capacity ($\bar{Q}$). The total irrigated area is calculated as the agent's total farm area ($\bar{A}$) minus the total area planted in dryland crops. c represents the cost of pumping a unit volume of groundwater and is assumed to be constant, as previous studies have shown that changes in groundwater depth have a small influence on agents' decisions compared to well capacity variations (Foster et al., 2015; Hrozencik et al., 2017; Mulligan et al., 2014). The production function f_m generates the crop yield per unit land area for dryland crop m based on seasonal weather realizations and soil type. Finally, h_n and h_m represent the fixed production costs per unit land area for irrigated crop n and dryland crop m , respectively. Crop prices, fixed production costs, and pumping costs are assumed to be constant throughout the simulation period. For detailed information on the values and estimation of these parameters, see Table B3 in Appendix B.

Once crops are planted and irrigation strategies are determined at the beginning of a growing season, it is assumed that agents will not alter these decisions during the season. The next step in the agents' decision-making process involves the realization of actual weather conditions throughout the growing season, using daily climate data specific to that season. Agents then make intraseasonal irrigation decisions based on daily variable soil water content and the pre-selected values of PAW_c and IFREQ. This approach offers a more accurate representation of actual irrigation planning compared to estimating total seasonal irrigation use (Foster et al., 2014). At the end of the growing season, the realized profit for each agent is calculated by determining the realized crop yields, total irrigation use, and subtracting the associated pumping and production costs from the gross revenue.

4.2.4. Hydrologic Model

The hydrologic model, referred to as the MODFLOW model hereafter, is constructed using the U.S. Geological Survey's MODFLOW-NWT model (Niswonger et al., 2011). The MODFLOW model includes groundwater storage and flow within the model domain and across the boundaries, surface water-groundwater interactions, pumping, recharge, and groundwater ET. It is discretized horizontally using a grid composed of uniform 500 m × 500 m cells arranged in 252 rows and 420 columns (Figure 3.4 in Chapter 3). It is a single-layer unconfined model, consistent with previous groundwater models developed for the HPA (e.g., Liu et al., 2010; Peterson et al., 2016; Republican River Compact Administration, 2003). The MODFLOW model comprises a total of 105,840 cells, with 83,713 active cells (variable head) and 22,127 inactive cells (no-flow).

The simulation period of the MODFLOW model is divided into two periods: the steady-state predevelopment period, representing the time before May 1st, 1946, and the transient post-development period, covering May 1st, 1946 to September 30th, 2018. Since pumping for irrigation is the primary stress in the study area, each 365-day in the post-development period is divided into two stress periods: a 153-day pumping period from May to September and a 212-day (or 213-day in leap years) recovery period from October to April. Stress periods are defined as periods during which system stresses, such as pumping and recharge, remain constant. A daily time step is considered for all stress periods in the model. To generate the MODFLOW model input files and facilitate post-processing, the Python package FloPy (Bakker et al., 2016) is utilized.

The MODFLOW model is calibrated using the Parameter Estimation software suite (PEST; Doherty, 2018). The simulation period is divided into a calibration period (predevelopment to

2010) and a testing period (2010 to 2018). In this study, we adjust a total of 49 parameters during calibration to achieve a satisfactory match between simulated and measured data. Calibration targets are measured groundwater levels and estimated stream baseflows. For details on estimating baseflows using measured daily streamflow data, see Section 3.6 in Chapter 3.

The MODFLOW model is constructed and calibrated prior to its integration into the hydro-economic modeling framework. To estimate the pumping rate of irrigation wells for the MODFLOW model, we pair groundwater-fed irrigated parcels with their corresponding irrigation wells and estimate irrigation requirements in the parcels using the FAO-56 method (Allen et al., 1998) from 1946 to 2018 (Section 3.5.4.3 in Chapter 3). To improve the accuracy of irrigation requirement estimates, we incorporate annual rasters of irrigated lands generated from remote sensing data and classification techniques for the 1984-2017 period (Deines et al., 2019). This integration of remotely sensed data to estimate irrigation requirements in irrigated parcels leads to a modified version of the MODFLOW model, referred to as the MODFLOW-RS model from here on.

For simulating the period before 1984, only the MODFLOW model is in use. Starting from 1984, the MODFLOW model branches into three distinct models: the hydro-economic model, which integrates MODFLOW with the economic and agronomic models, the standalone MODFLOW, and the MODFLOW-RS. In the Results section, we evaluate the performance of the hydro-economic model against both the MODFLOW and MODFLOW-RS models. For all models, the pumping rate for non-irrigation wells is determined by dividing each well's maximum annual appropriation volume by the total days in a year, assuming that these wells operate throughout the year. All details about the MODFLOW model are provided in Chapter 3.

4.2.5. Model Integration

Before exploring the model integration process, it is important to introduce the dynamic feedbacks between agents' decisions and the groundwater system that are captured within our hydro-economic modeling framework. Considering a representative agent depicted in Figure 4.3c, the agent's decisions on planting and irrigation strategies are based on parcel and well characteristics, such as soil type and well capacity. These decisions, combined with seasonal weather realizations, determine the required groundwater extraction for irrigation. While some of the pumped groundwater returns to the water table as irrigation return recharge and irrigated lands also enhance precipitation recharge, a significant portion is not replenished, leading to a decrease in the aquifer's saturated thickness. This decrease in saturated thickness negatively affects the capacity of the agent's well and the wells of neighboring agents. As a result, their future decisions are influenced, since lower well capacities cannot support as many irrigated areas.

To estimate the relationship between declines in saturated thickness and changes in well capacity, we use rasters of bedrock elevation and measured groundwater levels (Section 3.4 in Chapter 3), computing saturated thickness for each irrigation well from 1946 to 2018. Well capacity values at the time of well completion and pump installation are obtained from the CDSS. While well capacity can also vary with the age of the well due to factors like well screen clogging over time, our focus here is solely on variations in well capacity related to saturated thickness. Thus, we specifically select well capacity records at the time of well completion for our analysis. By computing changes in measured well capacity for wells with multiple records (reconstructed wells) and corresponding changes in saturated thickness, we derive an empirical equation for updating well capacity using a univariate linear regression model (Figure 4.4a):

$$Q_j - Q_i = 1.59 \frac{Q_i(b_j - b_i)}{b_i} \quad (4.4)$$

where Q_i and Q_j denote the well capacity of a given well at times i and j , respectively, while b_i and b_j represent the corresponding aquifer saturated thickness. To evaluate Equation (4.4), we incorporate additional well capacity data obtained during meter verification from the CDSS. Fitting a linear regression model to these new data (Figure 4.4b), we observe a disparity between the new regression coefficient and the one in Equation (4.4). Subsequently, we identify and remove outliers based on Cook's distance values of observations (Cook, 1977). Fitting a linear regression model to the data without outliers (Figure 4.4c), we find that the regression coefficient closely approximates the coefficient in Equation (4.4), while R^2 increases. This sequential analysis confirms the credibility of Equation (4.4). It is worth pointing out that a quadratic term is considered for saturated thickness in previous literature (Manning et al., 2020). However, given its lack of statistical significance, we opt to focus on the linear relationship.

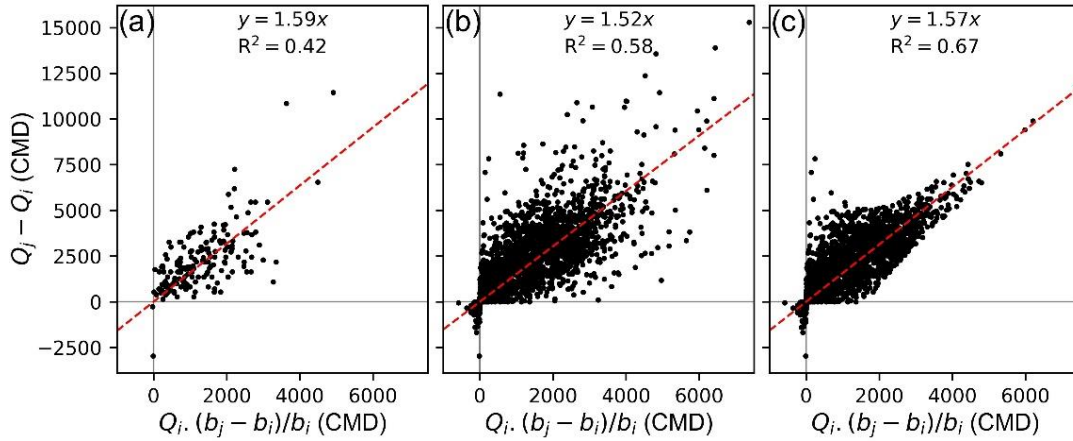


Figure 4.4. Relationship between well capacity (Q) and aquifer saturated thickness (b) at times i and j based on: (a) Well capacity records at the time of well completion, (b) Well capacity records obtained during meter verification and those included in panel a, and (c) Data from panel b without outliers. Note: 1 CMD (cubic meters per day) is equal to 0.1835 GPM (gallons per minute).

The integration process involves the agronomic model (DSSAT), the economic model, and the hydrologic model (MODFLOW), along with a set of Python post-processing scripts, all integrated through a Windows batch script (Figure 4.5). In this process, rather than fitting polynomials to DSSAT simulation outcomes to generate production functions (Hrozencik et al., 2017), we store DSSAT outputs (i.e., crop yields and irrigation use) for various combinations of soil type, weather realizations, crop type, PAW_c , and IFREQ in a production outcome library. This library is then utilized by the economic model to identify planting and irrigation decisions that maximize expected profit for each combination of total well capacity, soil type, and total quarter circle count, representing total farm area. The economic model explores a range of total well capacity values from 0 to 54,510 CMD (cubic meters per day), equivalent to 10,000 GPM (gallons per minute), with increments of 109 CMD (20 GPM). The model also assesses total quarter circle counts ranging from 1 to 37.

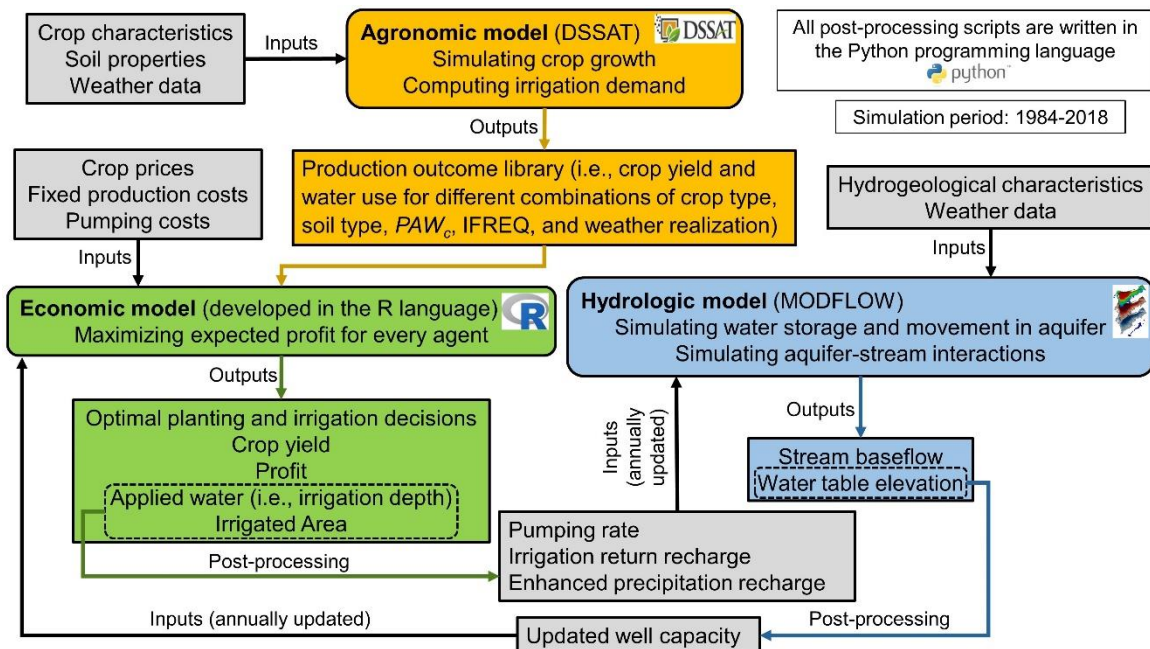


Figure 4.5. Hydro-economic modeling framework; PAW_c and IFREQ represent critical plant available water and irrigation frequency, respectively.

Optimal planting and irrigation decisions encompass the crop choices and PAW_c values that agents select at the beginning of the growing season and then adhere to throughout the season. Subsequently, the economic model generates realized crop yield, seasonal irrigation use, and profit for each optimal decision set in each year from 1984 to 2018. These results are then summarized in a lookup table. The lookup table enables us to solve the problem of maximizing expected profit (Equation (4.3)) for different combinations only once at the beginning of the simulation. It also facilitates tracking shifts in agents' decisions.

Seasonal simulations from 1984 to 2018 commence with the economic model first finding optimal planting and irrigation decisions for each agent in the lookup table based on the distribution of weather outcomes, and then providing the values of crop yield, profit, and seasonal irrigation use for the realized weather. Post-processing scripts convert seasonal irrigation depths to volumes, calculate total pumping volume for each agent, and allocate it proportionally among the agent's irrigation wells based on their current capacity values. Seasonally averaged pumping rates are then computed by dividing the pumping volumes by the duration of the pumping stress period in the MODFLOW model.

Irrigation return recharge is calculated as a percentage of the seasonal applied irrigation, which varies based on the type of irrigation system (Table 3.4 in Chapter 3). To maintain consistency with DSSAT simulations, we consider center pivot irrigation system for all agents throughout the simulation period. The irrigation return value is determined to be either 7% or 9%, depending on the specific type of center pivot system. Additionally, irrigated areas are identified based on agents' planting decisions, and in these areas, the precipitation recharge during the pumping stress period is enhanced by a factor of 2.88. The precise locations where irrigation return recharge and enhanced precipitation recharge reach the water table are determined by mapping the

parcels onto the MODFLOW model cells. See Figure B3 in Appendix B for the spatial distribution of average recharge during the recovery and pumping stress periods, as computed by the hydro-economic model. Detailed information about the calculation of enhanced precipitation recharge and irrigation return recharge can be found in Sections 3.5.6.1 and 3.5.6.2 of Chapter 3.

The input files of the MODFLOW model are updated with the new values of pumping rate, irrigation return recharge, and enhanced precipitation recharge. Once these updates are made, the MODFLOW model is executed for the pumping stress period and the subsequent recovery stress period, calculating groundwater levels and stream baseflows on a daily basis. In the following post-processing step, well capacity values are updated for the next growing season using Equation (4.4) and the computed groundwater levels on the last day of the recovery period. These updated well capacity values are then transferred to the economic model, which utilizes them to make decisions regarding planting and irrigation for the next growing season. This entire process is repeated for every growing season.

4.3.Results

In this section, we present outputs from our hydro-economic model, called the ABM-MODFLOW model henceforth. We start by assessing its accuracy in computing annual withdrawals from irrigation wells, a process influenced by all three components of the model, and compare this to the MODFLOW and MODFLOW-RS results. Next, we examine the hydrologic outputs, comparing the ABM-MODFLOW's performance against the other two models. We also evaluate its agronomic outputs, comparing simulated crop yields to agricultural survey data. Additionally, we validate the model's economic component, matching simulated planting decisions with actual data. Finally, we elucidate system dynamics using the ABM-MODFLOW outputs.

4.3.1. Groundwater Withdrawals

Groundwater extraction for irrigation is the primary human-induced stress on the groundwater system. The key distinction between the ABM-MODFLOW, MODFLOW, and MODFLOW-RS models lies in how they account for this stress. To begin the model validation process, we compare the groundwater withdrawals computed by each model for individual irrigation wells to values reported in CDSS and WIMAS (Figure 4.6a). The data for this comparison span the 2000-2018 period, constrained by data availability.

The distributions of residuals (errors), defined as simulated minus reported values, show that the ABM-MODFLOW model has a marginally better performance than the other two models. Comparing the performance metrics presented in Figure 4.6a, the ABM-MODFLOW model has a lower root mean square error (RMSE), while the MODFLOW-RS model shows slightly better results in percent bias (PBIAS) and Kling-Gupta Efficiency (KGE; Gupta et al., 2009). These results underscore the appropriate performance of the ABM-MODFLOW model, particularly given the meticulous approaches adopted to estimate groundwater withdrawals in the other two models. Notably, the MODFLOW-RS model leverages remote sensing data to determine the irrigation status of parcels in each year.

Discrepancies in the estimation of groundwater extraction affect the groundwater budget components (Figure 4.6b). The MODFLOW model's overestimation of withdrawals leads to increased pumping and groundwater depletion along with elevated recharge from increased irrigation return flows and augmented precipitation recharge. It also results in reduced groundwater discharge into streams due to declined groundwater levels. Figure 4.6b indicates that most components of the groundwater budget in the ABM-MODFLOW model are positioned between the MODFLOW and MODFLOW-RS models, highlighting its intermediate performance. Figure

B4 in Appendix B provides further relevant details on the ABM-MODFLOW model, including the percentage distribution of groundwater extraction for different uses and annual groundwater budget.

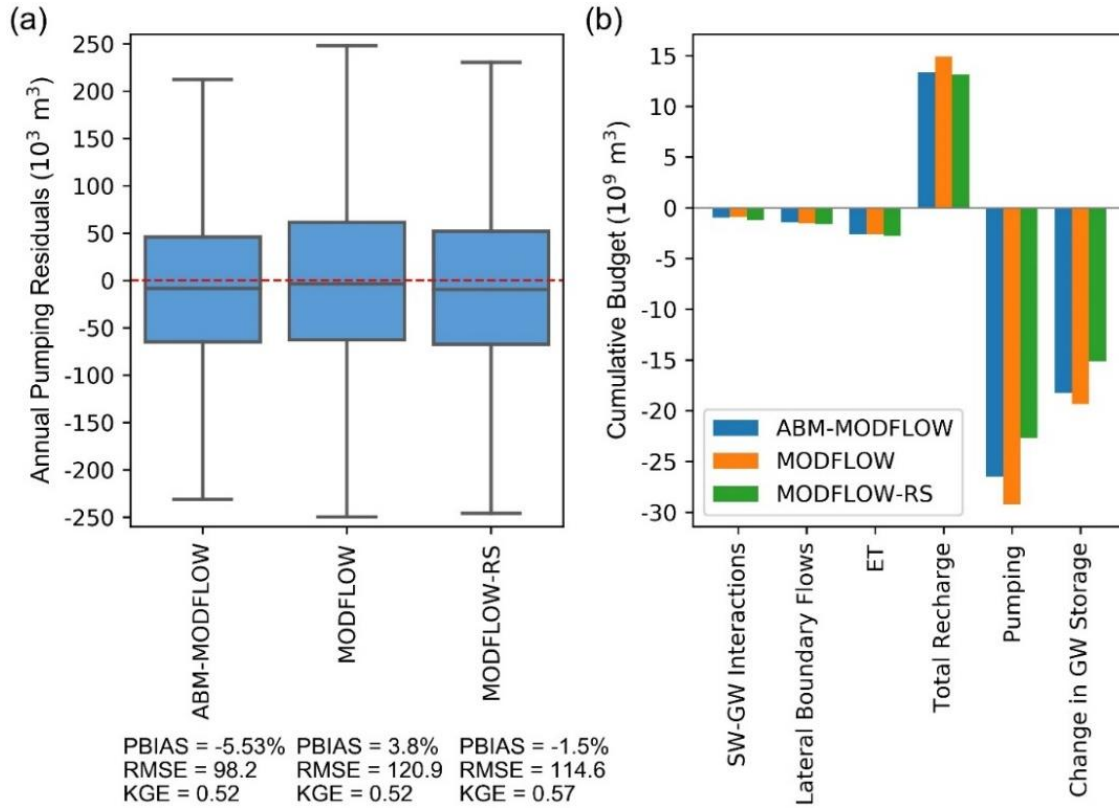


Figure 4.6. (a) Distribution of residuals (simulated minus reported values) for annual pumped water from individual irrigation wells during the 2000-2018 period for the ABM-MODFLOW, MODFLOW, and MODFLOW-RS models. (b) Cumulative groundwater budget for each model between 1984 and 2018. Note: RMSE is expressed in 10^3 m^3 and 10^3 m^3 is equal to 0.81 ac-ft.

4.3.2. Groundwater Levels and Stream Baseflows

Figure 4.7 displays the hydrographs of groundwater levels and average baseflows for April and October, as simulated by the ABM-MODFLOW model, alongside the measured (or estimated) data in multiple wells and stream gauges across the study area (see Figure 4.1b for locations). April and October are representative of high and low baseflow periods, respectively. A vertical dotted

line distinguishes data prior to 1984, since results prior to this year come from the standalone MODFLOW model. Hydrographs generated by the MODFLOW and MODFLOW-RS models are presented in Figures 3.17 and 3.18 of Chapter 3.

The ABM-MODFLOW model fairly reproduces the general trends observed in all the wells and gauges, with R-values above 0.7 everywhere, except for well 1 and gauges C and D (Figure 4.7). However, it fails to capture the flattening trend of groundwater level declines seen in wells 2, 4, 5, 6, and 7, mainly from the mid-1980's to the mid-1990's. This trend is associated with a significant decrease in irrigated lands, particularly in Kit Carson County in Colorado and Sherman and Cheyenne counties in Kansas. This is corroborated by both remote sensing data (Deines et al., 2019) and the Agricultural Census (U.S. Department of Agriculture, 2019c). The underlying cause for this decrease remains unknown to us and hence is not incorporated in the ABM-MODFLOW model. Conversely, the MODFLOW-RS model successfully replicates this specific trend.

A comprehensive performance evaluation of the ABM-MODFLOW model, focusing on groundwater levels and their changes, is detailed in Table 4.2. As simulation progresses, metric values deteriorate due to cumulative errors; however, the rate of performance decline either slows considerably or reverses in the last two simulation periods for all metrics, highlighting the model's stability. The ratios of both mean absolute error (MAE) and RMSE to the range of measured data consistently stay below 1%, indicating satisfactory model performance. However, the bias values show that the ABM-MODFLOW model tends to underestimate groundwater levels during the 1980-1990 and 1990-2000 periods, which coincide with a marked decrease in irrigated lands across the region. The model's inability to account for this decrease results in the overestimation of groundwater withdrawals.

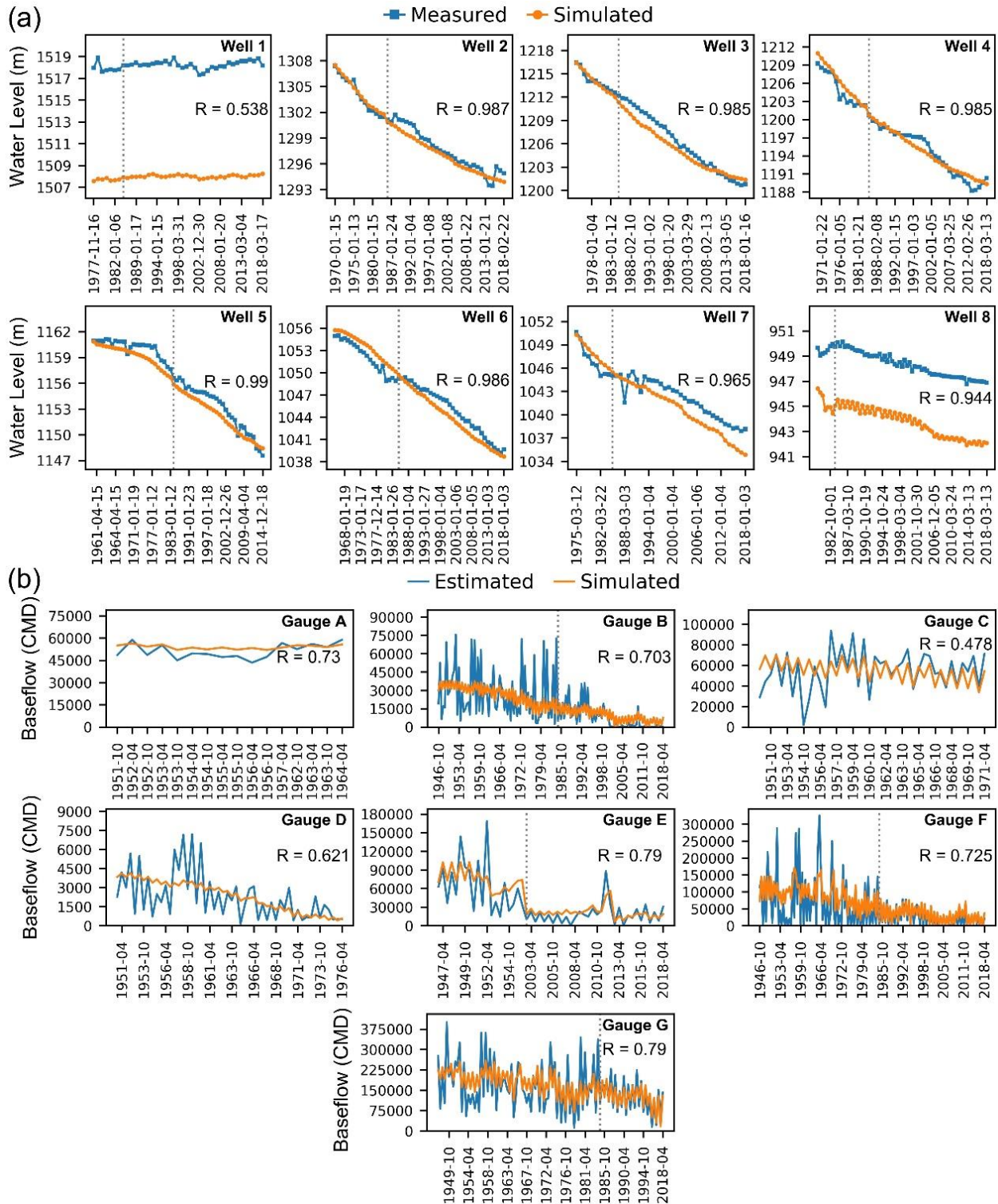


Figure 4.7. Hydrographs for various wells and stream gauges, comparing measured (or estimated) data with simulated values from the ABM-MODFLOW model. Vertical dotted lines separate data before 1984, as results are generated by the standalone MODFLOW model prior to this year. (a) Groundwater levels. (b) Average baseflows for April and October. Note: 1 m is equal to 3.28 ft and 1 CMD (cubic meters per day) to 0.00041 CFS (cubic feet per second).

Table 4.2. Models' performance metrics for groundwater levels and their changes.

Output Variable	Period	Number of Data	Model	Bias (m)	MAE (m)	RMSE (m)
Water Level	Predevelopment	982	MODFLOW	-0.03	4.27	6.03
Water Level	1946-1960	1,161	MODFLOW	-0.19	3.40	4.68
Water Level	1960-1970	4,062	MODFLOW	-0.86	3.67	4.83
Water Level	1970-1980	6,769	MODFLOW	-1.31	3.85	5.04
Water Level	1980-1990	4,976	ABM-MODFLOW	-2.76	4.67	5.88
			MODFLOW	-2.90	4.79	6.01
			MODFLOW-RS	-2.49	4.52	5.73
Water Level	1990-2000	5,404	ABM-MODFLOW	-3.80	5.44	6.57
			MODFLOW	-4.22	5.82	7.01
			MODFLOW-RS	-2.79	4.79	5.96
Water Level	2000-2010	5,297	ABM-MODFLOW	-3.47	5.40	6.63
			MODFLOW	-4.05	5.91	7.21
			MODFLOW-RS	-2.38	4.73	6.05
Water Level	2010-2018	4,450	ABM-MODFLOW	-3.30	5.41	6.94
			MODFLOW	-4.20	6.15	7.82
			MODFLOW-RS	-2.39	4.96	6.57
Water Level Change (5-yr interval)	1984-2018	16,635	ABM-MODFLOW	-0.17	0.91	1.45
			MODFLOW	-0.31	0.94	1.48
			MODFLOW-RS	-0.05	0.81	1.37

Note: Saturated thickness at measurement points during the predevelopment period varies from 0.5 to 91 m, with an average of 33 m. Measured groundwater levels from predevelopment to 2018 range from 900 to 1704 m. 1 m is equal to 3.28 ft.

For a broader assessment, we compare the ABM-MODFLOW model's performance against two regional MODFLOW models developed for the HPA, namely the Northern High Plains model (NHP; Peterson et al., 2016) and the Southwest Kansas model (SWK; Liu et al., 2010). In terms of RMSE, MAE, and bias, the ABM-MODFLOW model performs better, similarly, and poorer than the highly parameterized NHP model, respectively. When benchmarked against the SWK model in computing groundwater level changes, the ABM-MODFLOW model

outperforms in all metrics. This is especially notable considering that the SWK model is calibrated against changes in groundwater levels.

Performance metrics for groundwater levels and their changes rank the MODFLOW-RS highest, followed by ABM-MODFLOW, with standalone MODFLOW at the bottom (Table 4.2). A well-level analysis of metrics during the 2010-2018 period further supports these rankings (Figure 4.8). While the MODFLOW-RS model consistently excels, the ABM-MODFLOW model outperforms the MODFLOW model in Kit Carson County, Colorado, marked by lower well capacities (Figure B5 in Appendix B). The MODFLOW model's neglect of well capacity as a constraint on instantaneous water availability results in overestimated groundwater withdrawals. In contrast, the ABM-MODFLOW model lags behind the MODFLOW model in Cheyenne County, Kansas, primarily due to its inability to account for significant non-irrigated parcels during the mid 1980's to mid 1990's. Coupled with the county's high well capacities, this leads to the overestimation of groundwater extraction.

The performance metrics for average stream baseflows in April and October suggest a satisfactory performance by the ABM-MODFLOW model (Table 4.3). Specifically, KGE values for all gauges are greater than or equal to 0.45, and RMSE ratios to the estimated baseflow range remain below 20% across all gauges. PBIAS values indicate either very good or nearly satisfactory performance for all gauges, with the exception of gauge F (Moriasi et al., 2015). While PBIAS values suggest that the ABM-MODFLOW model tends to overestimate baseflows, its performance is deemed satisfactory. This is due to the absence of a surface water component, which would simulate water losses in streams through evaporation or riverbank seepage.

Per Table 4.3, the ABM-MODFLOW model has slightly better and identical performance compared to the MODFLOW-RS and MODFLOW models, respectively. This underscores the

reliability of the ABM-MODFLOW, especially since the hydrologic parameters are calibrated solely for the standalone MODFLOW model. For a detailed performance evaluation of the MODFLOW and MODFLOW-RS models, see Section 3.8 of Chapter 3.

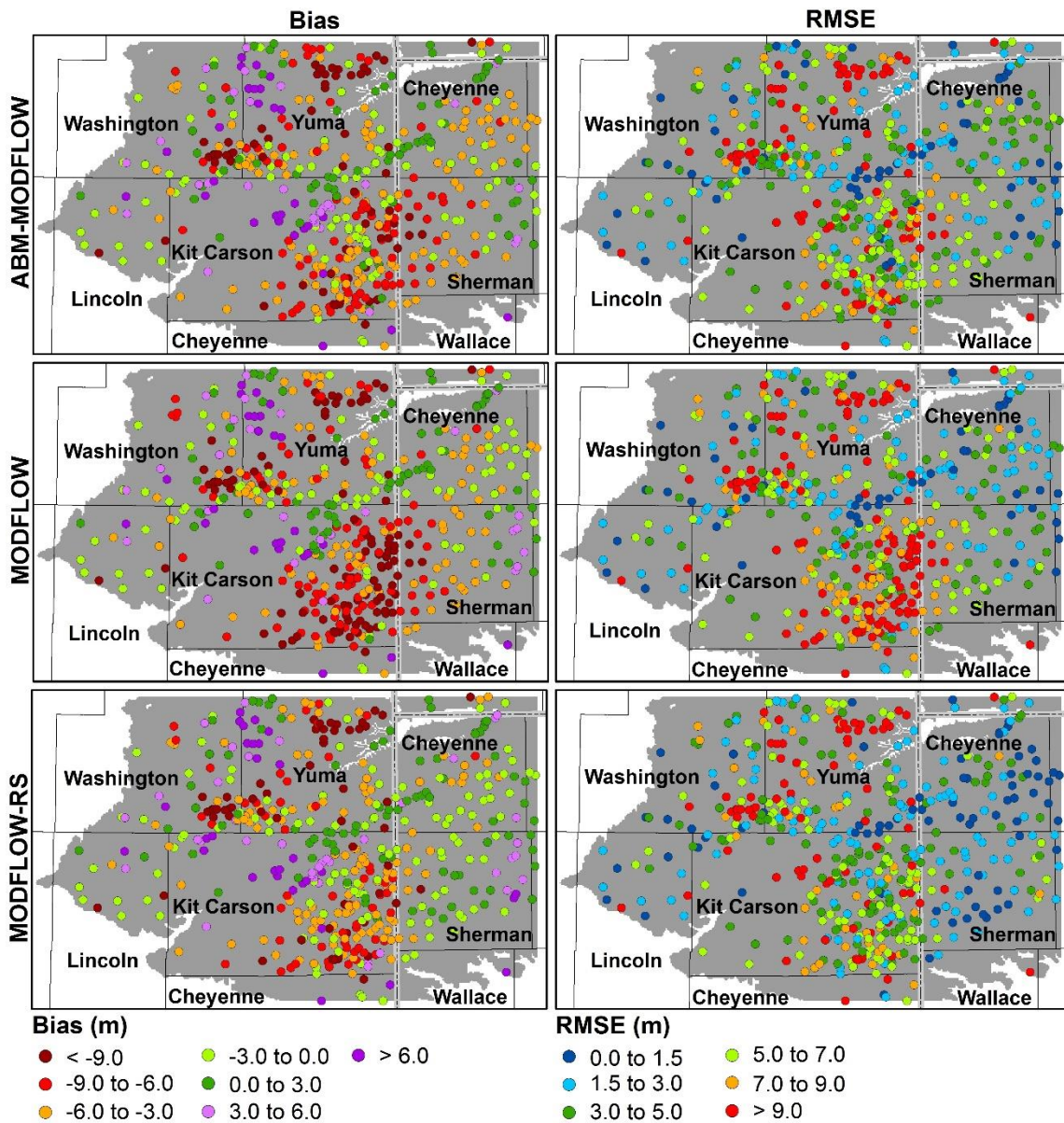


Figure 4.8. Models' performance metrics for individual wells during the 2010-2018 period. Note: 1 m is equal to 3.28 ft.

Table 4.3. Models' performance metrics for average stream baseflows in April and October.

Stream Gauge	Period of Data	Number of Data	Min Estimated Baseflow* (CMD)	Max Estimated Baseflow* (CMD)	Model	PBIAS	RMSE (CMD)	KGE
Gauge A (USGS 06822000)	1951-1964	16	43,412	58,810	MODFLOW	5.44%	4,739	0.24
Gauge B (USGS 06821500)	1946-2018	144	0	75,730	ABM-MODFLOW	1.57%	13,953	0.48
					MODFLOW	-0.41%	13,970	0.48
					MODFLOW-RS	6.46%	14,125	0.44
Gauge C (USGS 06825000)	1950-1971	42	1,920	93,689	MODFLOW	0.04%	17,054	0.29
Gauge D (USGS 06825500)	1950-1976	52	148	7,200	MODFLOW	2.89%	1,433	0.48
Gauge E (USGS 06827000)	1946-1956 & 2002-2018	52	406	168,563	ABM-MODFLOW	16.98%	22,990	0.66
					MODFLOW	15.46%	22,922	0.68
					MODFLOW-RS	21.15%	23,279	0.63
Gauge F (USGS 06827500)	1946-2018	144	0	325,565	ABM-MODFLOW	33.15%	48,916	0.45
					MODFLOW	34.10%	49,033	0.44
					MODFLOW-RS	41.45%	50,273	0.37
Gauge G (USGS 06824500)	1947-1995 & 2014-2018	105	11,750	400,919	ABM-MODFLOW	4.39%	56,929	0.54
					MODFLOW	3.38%	56,854	0.56
					MODFLOW-RS	4.87%	56,905	0.54

* April and October averages estimated based on measured daily streamflow data. 1 CMD (cubic meters per day) is equal to 0.000409 CFS (cubic feet per second).

4.3.3. Crop Yields and Irrigation Use

In Figure 4.9, we compare time series of crop yields simulated by the ABM-MODFLOW model to data from the National Agricultural Statistics Service (NASS; U.S. Department of Agriculture, 2019d). Simulated dry mass crop yields are converted to moist yields within the ABM-MODFLOW model, assuming moisture content values of 15.5% for corn and 13.5% for winter wheat. Since NASS data are provided at the county-level, both simulated and NASS yields are averaged across three counties that lie entirely within the model domain, namely Kit Carson in Colorado, and Cheyenne and Sherman in Kansas. Performance metrics presented in Figure 4.9 are

computed for years after 1991, given the improved quality of relative humidity, solar radiation, and wind speed data. Overall, the model simulates crop yields with reasonable accuracy, achieving KGE values greater than or equal to 0.12, despite not accounting for factors like cultivar improvement, inadequate soil nutrients, pests, diseases, and hail.

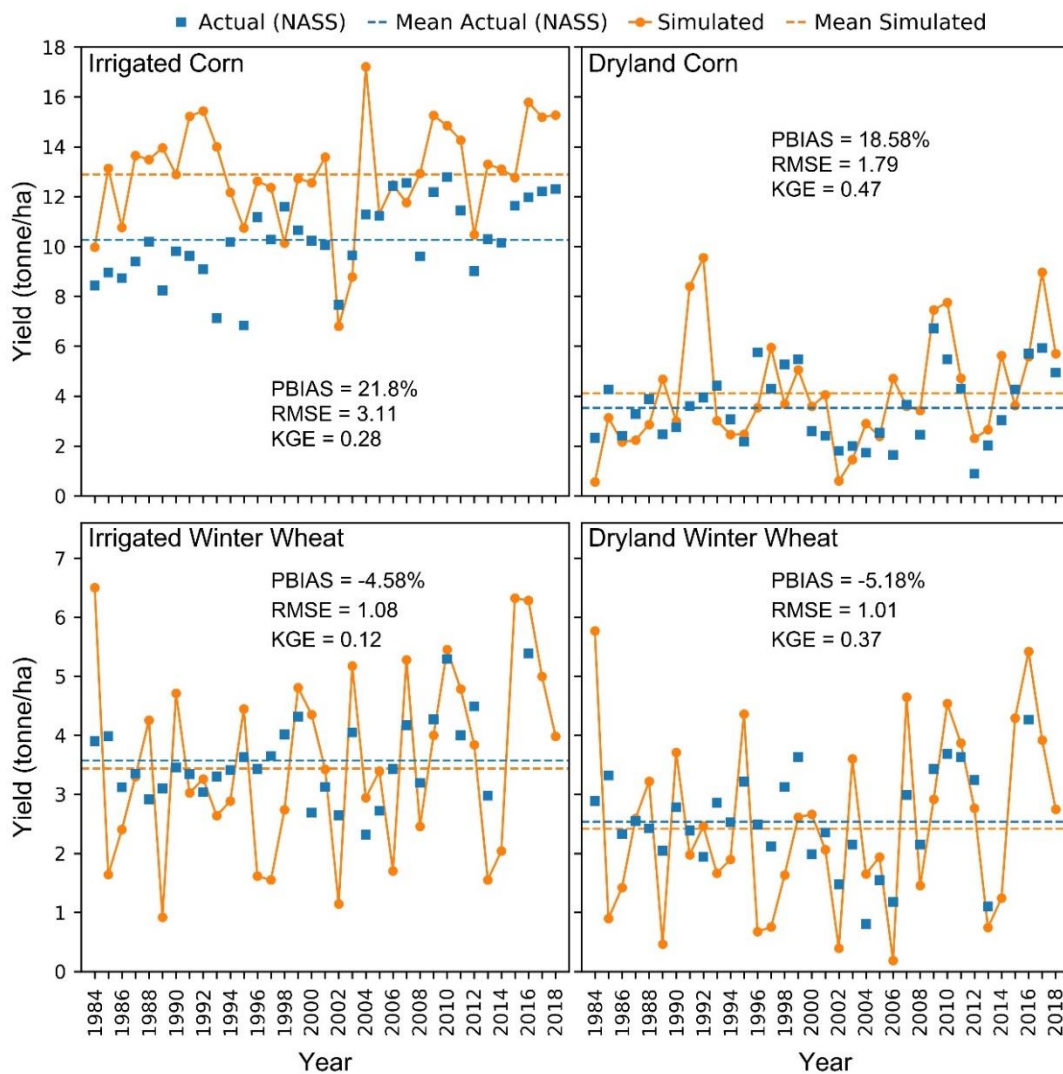


Figure 4.9. Time series comparing the ABM-MODFLOW model's simulated crop yields with NASS data, averaged over Kit Carson County in Colorado, and Cheyenne and Sherman counties, Kansas. Note: Performance metrics span the 1992-2018 period. RMSE is expressed in tonne/ha and 1 tonne/ha of corn is equal to 15.93 bu/ac and 1 tonne/ha of winter wheat to 14.87 bu/ac.

While the ABM-MODFLOW model tends to overestimate both irrigated and dryland corn yields, PBIAS values indicate satisfactory performance for all crops (Wang et al., 2012). The model's reduced accuracy for irrigated crops can be ascribed to the elevated uncertainties that exist in irrigated crop production. Under full irrigation, with PAW_c at 55% and IFREQ at 3, the average seasonal net irrigation requirement simulated for corn and winter wheat is 367 mm and 276 mm, respectively. In contrast, the suggested values for southwest Kansas are 406 mm for corn and 305 mm for winter wheat (Rogers, 2007, 1997; Rogers et al., 2015). Given the slightly lower irrigation requirements in northwest Kansas, the model's accuracy in simulating seasonal irrigation use is deemed appropriate.

4.3.4. Planting Decisions

To validate the economic component of the ABM-MODFLOW model, we compare the simulated irrigated area in Kit Carson County in Colorado, and Cheyenne and Sherman counties, Kansas, to county-level Agricultural Census data (Figure 4.10a; U.S. Department of Agriculture, 2019a). Excluding the census years of 1987 and 1992, during which many parcels were not irrigated, a strong correlation is evident between the simulated and census data, with an R-value of 0.838. Discrepancies may arise from the Agricultural Census's potential underreporting of actual irrigated lands (Dickens et al., 2011; McManamay et al., 2021). The spike in 2017 census data could be attributed to that year's record-breaking spring and summer precipitation, measuring 526 mm, considering the impact of precipitation on irrigation extent (Deines et al., 2017). Nonetheless, since the ABM-MODFLOW model determines optimal planting decisions based on expected values, it struggles to accurately replicate agents' decision-making under extreme conditions.

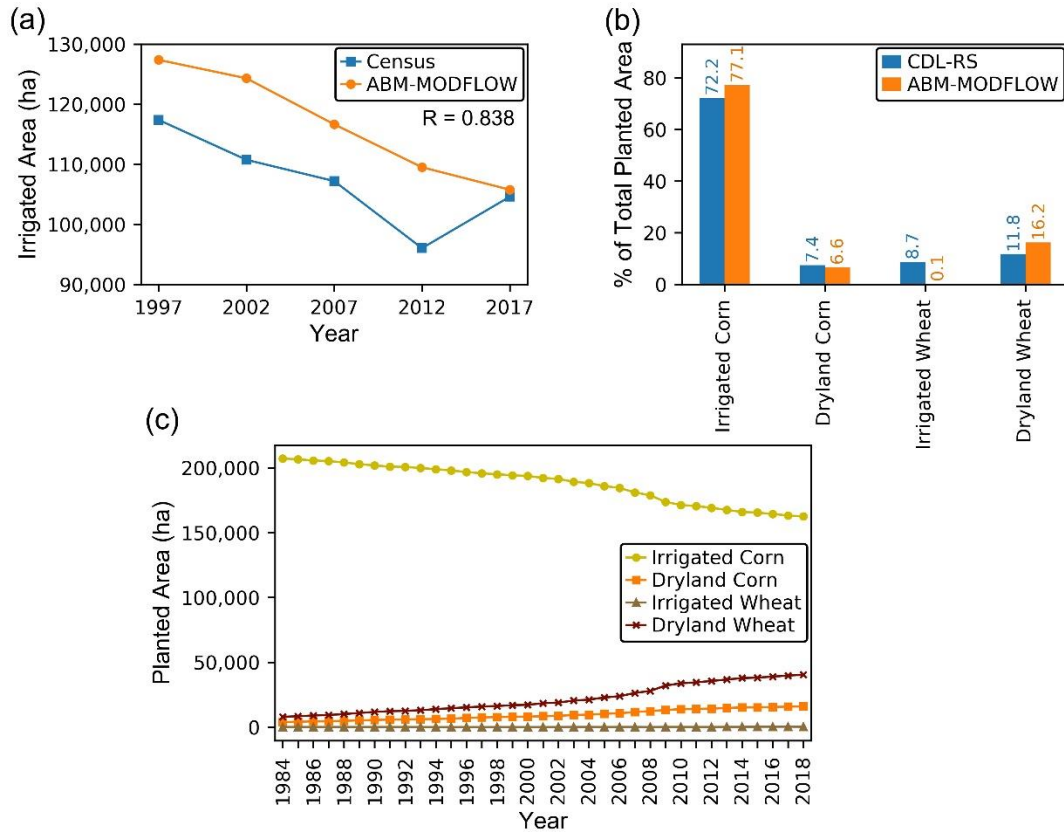


Figure 4.10. Planting decisions. (a) Comparison of the ABM-MODFLOW model’s simulated irrigated area with Agricultural Census data, aggregated for Kit Carson County in Colorado, and Cheyenne and Sherman counties in Kansas. (b) Percentage distribution of selected crops during the 2008-2017 period, as simulated by the model, alongside estimates derived from NASS Cropland Data Layers combined with remote sensing data (CDL-RS). (c) Time series of planted area with each crop across the study area, as simulated by the model. Note: 1 ha is equal to 2.47 ac.

To assess simulated crop choices, we estimate the area planted with each of the four crops in groundwater-fed irrigated parcels across the study area from 2008 to 2017, using the NASS Cropland Data Layers (CDL; Boryan et al., 2011; U.S. Department of Agriculture, 2019b) in conjunction with remote sensing data (Deines et al., 2019). Subsequently, we calculate each crop’s percentage distribution and compare it with simulated values (Figure 4.10b). While simulated crop choices align well with CDL-RS data overall, the ABM-MODFLOW model underestimates irrigated winter wheat. Given that winter wheat has the lowest irrigation value among major crops

in the HPA (Smidt et al., 2016), the model's reluctance to select it as an optimal choice is justifiable. This discrepancy might stem from inaccuracies in CDL and remote sensing data, or real-world farmers' sub-optimal decisions influenced by factors like crop rotation.

Figure 4.10c displays the time series of area planted with each crop in the study area, as simulated by the ABM-MODFLOW model. Given corn's significantly higher irrigation value compared to winter wheat (Smidt et al., 2016), it remains the agents' primary choice throughout the simulation period. However, since corn is water-intensive and well capacities are continually declining, agents begin allocating parts of their farms to other crops. Notably, there is a shift from irrigated corn to dryland corn and dryland winter wheat in Kit Carson County, Colorado (Figure B6 in Appendix B).

4.3.5. System Dynamics

We explore the impacts of groundwater availability and weather on profitability by analyzing profit distribution time series for agents grouped by their initial irrigation capacity (Equation 4.2) and the mean SPEI-3 values from May to September (Figure 4.11). SPEI-3 denotes the standardized precipitation evapotranspiration index (Vicente-Serrano et al., 2010) with a three-month aggregation period. It is a measure of agricultural drought (Zambreski et al., 2018), where negative and positive values indicate drier and wetter than normal conditions, respectively. Agents are classified into low, medium, and high initial irrigation capacities using the 33rd and 66th percentiles of the 1984 irrigation capacities. These percentiles correspond to 62 (4.60) and 91 (6.75) CMD/ha (GPM/ac), respectively. To provide context, these values respectively equate to irrigating a typical 52.61 ha (130 ac) circle using wells with capacities of 3,262 (598) and 4,788 (878) CMD (GPM).

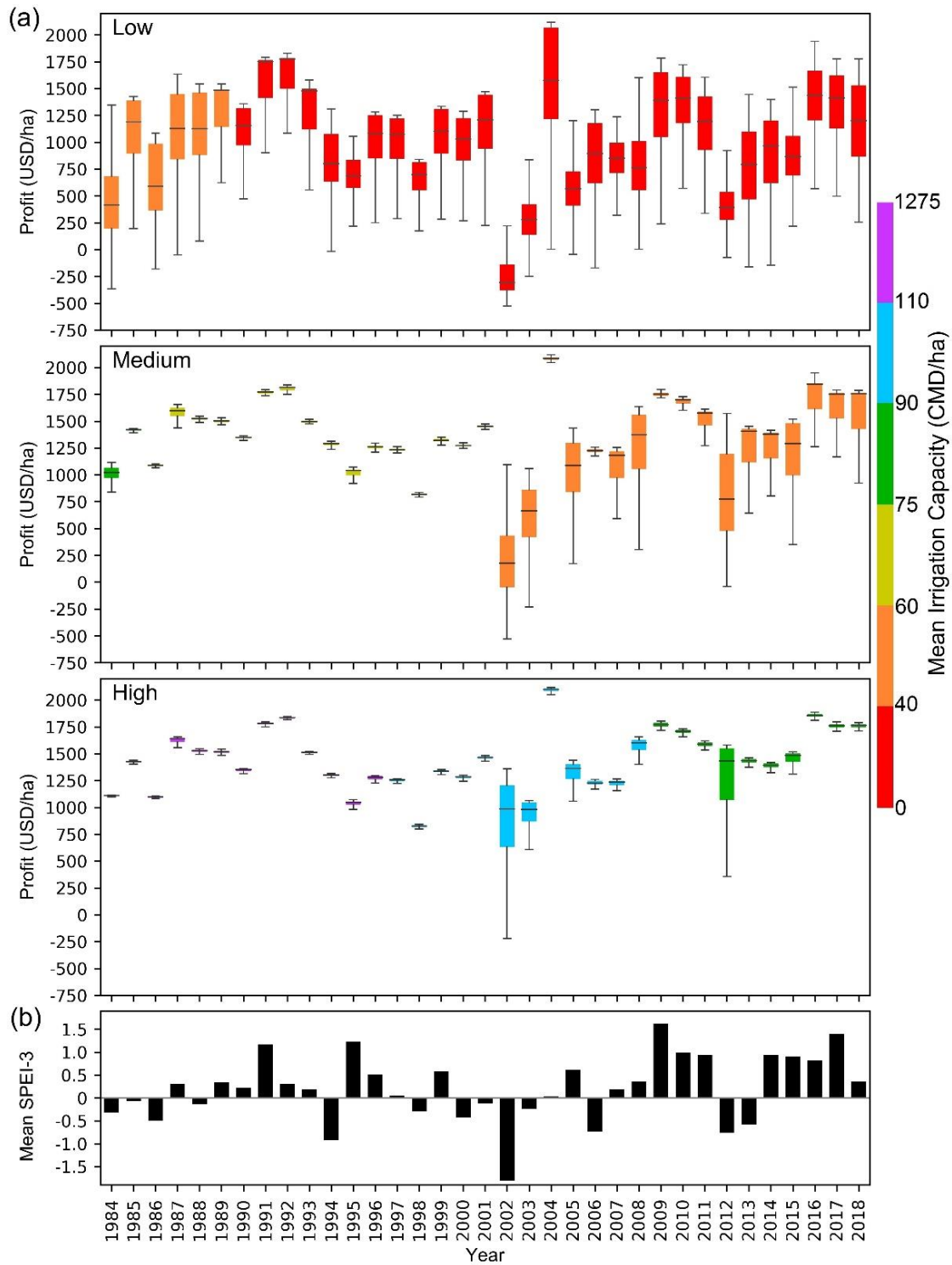


Figure 4.11. (a) Time series of profit distribution for agents with low (less than 62 CMD/ha), medium (between 62 and 91 CMD/ha), and high (greater than 91 CMD/ha) irrigation capacities in 1984. The color of box plots indicates the mean irrigation capacity for each year. (b) Time series of the mean SPEI-3 values during the growing season (May to September). SPEI-3 denotes the standardized precipitation evapotranspiration index with a three-month aggregation period. Note: 1 CMD/ha is equal to 0.074 GMP/ac and 1 USD/ha to 0.405 USD/ac.

In the low category, profits are smaller and exhibit greater variability in a given year than in the other two groups (Figure 4.11). This variability is primarily attributed to the pronounced influence of soils' capacity to store precipitation (i.e., green water) when groundwater availability is limited. Interestingly, profit variability diminishes in the exceptionally dry years of 2002 and 2012, as soil type becomes less influential under severe weather conditions. In the medium category, profits are slightly smaller than in the high group, with profit variability in a given year increasing over time due to declines in well capacities. This temporal trend, however, is not as marked in the high group. Profit variability in both the medium and high categories increases in 2002 and 2012, emphasizing the role of soil type during extreme weather conditions when irrigation capacity is sufficient.

For the high group, the variability in profits over time is smaller, with a standard deviation of annual median profits at 286 USD/ha compared to 379 and 438 USD/ha for the medium and low groups, respectively. It suggests that agents with lower irrigation capacities are more vulnerable against adverse weather conditions, resulting in higher production risk.

Figures 4.12a, 4.12b, and 4.12c display the spatial distribution of initial irrigation capacity, generalized soil categories, and average annual profit from 1984 to 2018, respectively. It is evident that in areas with limited irrigation capacities, such as Kit Carson County, agents tend to have the lowest profits. In regions such as Yuma County, which has high irrigation capacities but sandy soils, agents make profits comparable to those in areas like Sherman County. The latter has lower irrigation capacities but benefits from silt loam soils, which have a higher water-holding capacity. Figure 4.12d illustrates the combined impact of initial irrigation capacity and soil type on profitability. Agents with high irrigation capacities and fine soils achieve the highest profits, while those with low irrigation capacities and sandy soils earn the least.

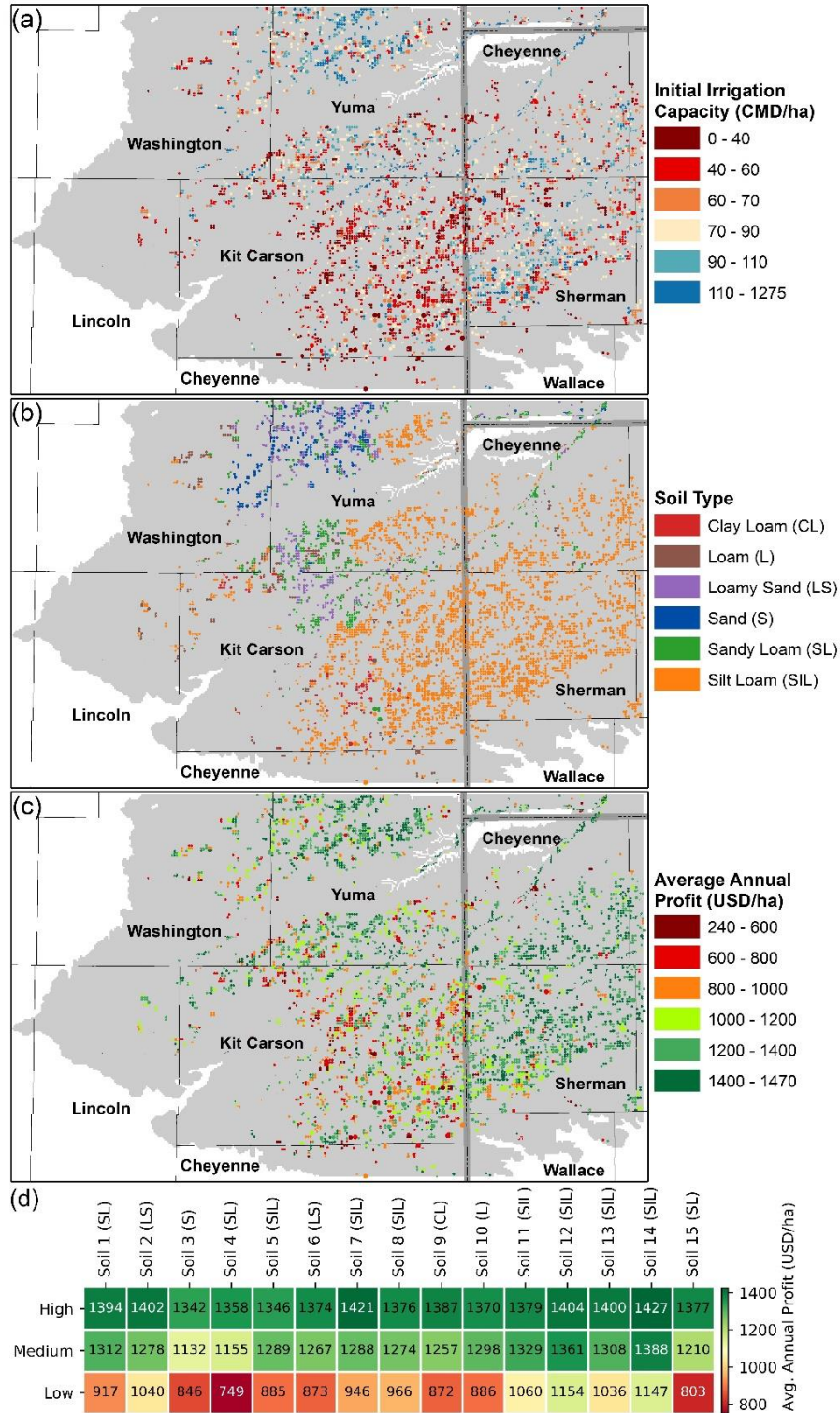


Figure 4.12. (a) Irrigation capacity in 1984. (b) Generalized soil categories. (c) Average annual profit from 1984 to 2018. (d) Average annual profit from 1984 to 2018 based on combinations of soil type and initial irrigation capacity categories. See Table 4.1 for soil names and properties. Note: 1 CMD/ha is equal to 0.074 GMP/ac and 1 USD/ha to 0.405 USD/ac.

4.4. Discussion

The comprehensive assessment of the ABM-MODFLOW model's outputs demonstrates its satisfactory performance in simulating various aspects of the coupled human-natural system, highlighting its dependability for evaluating different policy instruments. Additionally, when compared against the standalone MODFLOW model, integrating the groundwater model with economic and agronomic models does not compromise hydrologic outputs but rather enhances the precision of simulated groundwater levels. This improved precision chiefly stems from a more accurate calculation of withdrawals from irrigation wells.

In intensively groundwater-fed irrigated regions, determining groundwater extraction from irrigation wells remains a pivotal yet challenging phase in building groundwater models for both historical and future simulations. For historical simulations, measured pumping records are often unavailable, necessitating estimates. One way to approximate withdrawals from irrigation wells is by calculating the irrigation requirements of the associated irrigated lands. This approach, however, is hindered by the need for land use data, which often are not available at the desired spatial resolution for earlier years. For instance, CDL data for the conterminous U.S. exist only from 2008 onward. As a result, land use for previous years must be inferred using certain simplifying assumptions.

Similarly, for future simulations, land use must be projected to estimate irrigation requirements and the resultant groundwater withdrawals. However, agents' future planting decisions are driven by economic factors and are constrained by groundwater availability. Thus, to forecast land use and groundwater extraction reasonably, it is necessary to account for the coevolution of agents' decisions, crop yields, irrigation requirements, and the groundwater system. The ABM-MODFLOW model handles this complexity by simulating the planting and irrigation

decisions of agents, who represent their real-world counterparts. Such a feature makes it a suitable tool for simulating the groundwater system in both historical and future periods.

In recent years, numerous fully integrated models have emerged to simulate interactions between human activities and groundwater systems, with some models including surface water systems as well. However, many of these models exhibit limitations in capturing the complex details necessary for hydro-economic modeling and analysis. For instance, FlowLogo (Castilla-Rho et al., 2015) omits the simulation of crop growth and development processes and does not consider well capacity as a factor in agents' decision-making processes. MF-OWHM (Boyce et al., 2020; Hanson et al., 2014) neither simulates agents' planting decisions nor the processes of crop growth and development. Meanwhile, ABM-HEIFLOW (Du et al., 2022) employs a heuristic economic optimization approach to determine the source of irrigation for agents, neglecting to simulate their planting decisions. Thus, despite the value of these fully integrated models, their inherent limitations underscore the importance of modularly coupled models, such as ABM-MODFLOW, in the hydro-economic modeling of groundwater systems.

The analysis of system dynamics offers valuable policy insights. Among agents with low irrigation capacity, there is high variability in annual profits, suggesting a need for spatially heterogeneous policy designs for this group. Conversely, given the considerable administrative and enforcement costs associated with heterogeneous policies and lower variability in annual profits among agents with medium or high irrigation capacities, implementing uniform conservation policies for these agents might be more efficient. Moreover, water conservation policies could pose higher costs for agents with coarser soils, due to these soils' limited capacity to store precipitation water. Therefore, when formulating policies, it is crucial to account for soil type heterogeneity among agents.

While the ABM-MODFLOW model effectively reproduces historical data and trends, like any other model, it has certain limitations. First, it does not take into account potential sub-optimal planting and irrigation decisions made by agents. Second, the model overlooks occasional interruptions in irrigated crop production due to factors like crop rotation and maintenance. Consequently, its accuracy in predicting groundwater levels is slightly lower than the MODFLOW-RS model. Third, the ABM-MODFLOW model does not consider the impact of summer fallowing, common in dryland crop production, on planting decisions. Nonetheless, the significance of this exclusion is likely to decrease over time, in light of the trend towards more intensified rotations and continuous dryland cropping in the study area (Rosenzweig and Schipanski, 2019). Lastly, the model does not account for alternative transition pathways in planting decisions caused by groundwater depletion, such as transitioning from irrigated agriculture to pasture, particularly in areas with unsuitable soil types (Deines et al., 2020).

In future studies, the ABM-MODFLOW model can be utilized to evaluate the impacts of different policies on agents' profitability, groundwater storage, and stream baseflows. By adjusting the objective function (Equation 4.3), the model is capable of simulating a variety of policy instruments. These include tax policies, extensive cap policies (e.g., restricting irrigated area), and intensive cap policies (e.g., limiting the annual volume of pumped water).

There is also an opportunity to relax the model's assumption of agent risk-neutrality. This can be achieved by transitioning from an expected profit maximization procedure to a certainty equivalent maximization, which equals the expected profit minus the risk premium (Foster et al., 2014). With this modification, the model can account for behavioral heterogeneity among agents by specifying different values for the coefficient of risk aversion within the risk premium.

Although our sensitivity analysis is currently limited to the standalone MODFLOW model (Section S3.7 in Chapter 3), a global sensitivity analysis of the ABM-MODFLOW model would highlight the influence of different parameters and inputs on the model's outcomes as well as their interactions.

4.5. Conclusion

This research presents a detailed hydro-economic model, ABM-MODFLOW, designed to capture dynamic feedbacks within a coupled human-groundwater system in irrigated regions. Distinct to this study, each modeling component is developed through interdisciplinary collaboration to meet specific research objectives. A unique feature of our work is the attention to detail in the creation of agents, ensuring they closely represent real-world farmers. Furthermore, we incorporate well capacity as a constraint on the duration of irrigation applications, a factor predominantly overlooked in existing literature.

To the best of our knowledge, this is the first study to rigorously validate the outputs of a hydro-economic model with the aim of ascertaining its reliability for future analyses. Despite the inherent complexity of the system, the validation results are promising. The ABM-MODFLOW model effectively reproduces a suite of historical data, ranging from hydrologic outputs to crop yields and planting decisions. Additionally, our results highlight the enhanced accuracy of the hydrologic model once integrated with economic and agronomic components, largely attributed to improved estimates of groundwater extraction and recharge. This underscores the superiority of hydro-economic models over standalone groundwater models when simulating heavily utilized groundwater systems, both historically and for future projections.

Using model outputs to explore system dynamics, we observe higher profit variability among agents with low irrigation capacities, largely due to the pronounced influence of soil type. Conversely, less profit variability exists among agents with medium or high irrigation capacities, with exceptions in extremely dry years. Agents with high irrigation capacities tend to maintain consistent profits over time, since they can effectively buffer against dry conditions. Overall, agents with high irrigation capacities and fine soils earn the highest profits, whereas those with low irrigation capacities and coarse soils achieve the lowest.

In summary, our study underscores the merits of hydro-economic models as state-of-the-art tools for simulating the coevolution of agents' decisions, crop yields, irrigation requirements, and groundwater storage in intensively irrigated regions.

CHAPTER 5.

GROUNDWATER CONSERVATION IN THE FACE OF CLIMATE CHANGE: DYNAMIC HUMAN-CROP-GROUNDWATER INTERACTIONS IN SEMI-ARID REGIONS

Highlights

Persistent groundwater depletion in semi-arid agricultural regions poses a critical challenge, threatening both the livelihoods of rural communities and global food security. An effective solution may involve designing groundwater management policies that aim to reduce groundwater extraction, while minimizing associated economic costs over a multi-generational timeframe, all in the context of human-induced climate change. In semi-arid agricultural regions, the indirect impacts of climate change, such as shifts in irrigation demands and land-use change, are expected to have a greater effect on groundwater systems than direct impacts like variations in recharge rates. However, the existing hydrologic modeling literature often focuses only on the direct impacts, or, when evaluating the indirect impacts, fails to consider potential shifts in farmers' crop choices and irrigation strategies. While hydro-economic models show promise in simulating the indirect impacts of climate change on groundwater systems, they have yet to be employed to explore these impacts through a scenario-based approach. In this study, we employ an agent-based hydro-economic model (ABM-MODFLOW) to project the coevolution of human activities, crops, and groundwater in a semi-arid agricultural region in the U.S. High Plains amidst climate change, both with and without groundwater management. The ABM-MODFLOW simulations involve 32 climate scenarios from 16 downscaled global climate models for two representative concentration pathways, and evaluate three policy instruments, namely irrigated

land retirement, irrigation well retirement, and authorized pump rate reduction. The simulation outcomes reveal that the groundwater depletion rate decreases over time, primarily due to rising summer temperatures from climate change that limit corn production, a water-intensive crop, in the region. Moreover, these rising temperatures hamper the economic benefits of policies, since the early conserved groundwater is predominantly used for winter wheat irrigation in the later years, a crop with substantially lower irrigation value than corn.

5.1. Introduction

Irrigated agriculture has been established and maintained in semi-arid regions worldwide at the expense of significant groundwater depletion in several major aquifers (Famiglietti, 2014; Taylor et al., 2013). These aquifers include the High Plains and Central Valley in the United States, the North China Plain in China, and the Indus-Upper Ganges in India and Pakistan (Aeschbach-Hertig and Gleeson, 2012; Gleeson et al., 2012b; MacDonald et al., 2016). In these regions, irrigation relies on the extraction of non-renewable fossil groundwater (Wada et al., 2012). The persistent groundwater depletion in semi-arid regions threatens not only the livelihoods of rural communities dependent on irrigated agriculture for income and employment (Lauer et al., 2018), but also imperils global food security in the face of increasing food demand driven by population growth and dietary shifts (Aeschbach-Hertig and Gleeson, 2012; Famiglietti, 2014). Furthermore, groundwater depletion is anticipated to accelerate in these regions amidst climate change due to potential increases in irrigation demand and shifts from surface water to groundwater as the primary source of irrigation water (Cook et al., 2015; Liu et al., 2022; Taylor et al., 2013).

One significant cause of groundwater depletion is its nature as a common property resource. This results in the tragedy of the commons, where individual users excessively exploit the shared groundwater without incentive to limit their extraction to socially optimal levels,

ultimately leading to a market failure (Aeschbach-Hertig and Gleeson, 2012; Rouhi Rad et al., 2020a). Therefore, a potentially effective solution for groundwater depletion is to implement groundwater management policies that reduce irrigation water demand, prolong aquifers' lifespan, and sustain stream baseflows in the long-term, while minimizing the short-term economic costs associated with reduced water usage (Hrozencik et al., 2017; Whittemore et al., 2023).

Groundwater sustainability, with its multi-generational timeframe spanning 50 to 100 years (Gleeson et al., 2012a), must be viewed in the context of human-induced climate change. Climate change can influence groundwater systems directly through variations in groundwater evapotranspiration (ET) and recharge rates and/or indirectly through changes in groundwater extraction and land-use prompted by human activities (Scanlon et al., 2021; Taylor et al., 2013). Changes in groundwater extraction are mainly driven by shifts in irrigation demands and the sources of irrigation water. Land-use change can affect groundwater recharge by enhancing precipitation recharge in irrigated lands due to higher soil moisture (Cherry et al., 2020). It can also modify irrigation demands based on shifts in crop selection. In semi-arid agricultural regions, where groundwater is relatively deep and heavily extracted for irrigation, the indirect impacts of climate change on groundwater systems are expected to dominate direct impacts (Russo and Lall, 2017).

The existing hydrologic modeling literature, however, predominantly focuses on the direct impacts, particularly variations in recharge (Crosbie et al., 2011; Cuthbert et al., 2019; Niraula et al., 2017). While a few recent studies explore the indirect impacts (Chen et al., 2023; Kumar et al., 2023; Ou et al., 2018), they fail to account for potential shifts in farmers' crop choices and irrigation strategies driven by groundwater availability and climate-induced changes in crop profitability. Moreover, these studies do not consider any groundwater management policies in

their analysis. Among them, only Kumar et al. (2023) employ a crop simulation model to extensively assess the effects of climate change on crop water demands, particularly the enhancing impacts of elevated atmospheric carbon dioxide concentrations (CO_2) on crop water productivity (Deryng et al., 2016).

Hydro-economic models serve as advanced tools in the evaluation of water management policies, including those targeting groundwater, at a regional scale (Kahil et al., 2016). These models integrate neoclassical economics with hydrology, and often agronomy, within a coherent framework (Harou et al., 2009). In recent literature of hydro-economic modeling of groundwater systems in semi-arid regions, a variety of groundwater management policy instruments have been assessed. Some studies compare welfare gains achieved by centralized optimal control against decentralized scenarios, wherein individual farmers maximize their profits either autonomously or under policy instruments like uniform taxes or quantity restrictions (Guilfoos et al., 2013; Mulligan et al., 2014). Guilfoos et al. (2016) examine a broad array of policy instruments, including tax and quantity restrictions, as well as groundwater markets (i.e., trading water rights for groundwater extraction while keeping the total extraction restricted) implemented both at the aquifer-wide and local scales. Hrozencik et al. (2017) explore the heterogeneous impacts of uniform policy instruments, such as pumping fee, quantity restriction, and irrigated acreage fee, on farmers within a river basin. Khan & Brown (2019) compare the performance of groundwater markets to quantity restriction policy instruments under various climate scenarios, while Manning et al. (2020) quantify the economic benefits of a groundwater right retirement program for farmers.

While recent hydro-economic modeling studies provide valuable insights into different policy instruments, they often come with certain structural limitations that could compromise their reliability, as elaborated in Chapter 4. Many of these studies fail to incorporate appropriate

groundwater models; i.e., they are either overly simplistic or were originally developed for objectives other than hydro-economic modeling. Groundwater models play a pivotal role in policy evaluation, given that a policy's efficacy hinges on groundwater level changes in irrigation wells and the responsiveness (elasticity) of crop production and revenue to those changes (Manning and Suter, 2019). Additionally, the impact of prolonged irrigation application durations due to diminished well capacity is frequently neglected, leading to inaccurate predictions of crop yield, irrigation use, and profitability (Domínguez et al., 2022). This can result in underestimating both the costs of groundwater depletion and the benefits of its management. Lastly, the decision-making units in these studies are not representative of real-world farmers and their attributes, such as combined capacity of irrigation wells, total farm area, and dominant soil type. Since these attributes can influence the outcomes of groundwater management (Saak and Peterson, 2012), any misrepresentation may lead to erroneous policy evaluations.

Since hydro-economic models account for the interactions between climate, crops, human activities, and groundwater, they can be employed as valuable tools for simulating the indirect impacts of climate change on groundwater systems under both no-action (status quo) and policy scenarios. However, they have yet to be employed to study the impacts of climate change on groundwater systems using a scenario-based approach. In many prior hydro-economic modeling studies, future climate conditions are either assumed constant (Mulligan et al., 2014) or treated by repeating a historical weather cycle (Hrozencik et al., 2017; Manning et al., 2020; Rouhi Rad et al., 2020b). One study considers climate change by weighting historical weather data, making drier than average years progressively more probable (Aistrup et al., 2017). In another study climate change is incorporated through perturbing historical climate data based on future climate projections, but in the absence of a crop simulation model, it assumes that crop water requirements

change linearly with temperature (Khan and Brown, 2019). Notably, none of these studies account for the effects of increased CO₂ on crop yields and water use and subsequently on the crop-water production functions.

Our primary goal is to project the coevolution of human activities, crops, and groundwater in semi-arid agricultural regions amidst climate change, both with and without groundwater management. We employ a state-of-the-art hydro-economic model constructed for a portion of the U.S. High Plains Aquifer. This model, named the ABM-MODFLOW, has been developed and rigorously validated through interdisciplinary collaboration and overcomes structural limitations found in earlier models (Chapter 4). The ABM-MODFLOW is an agent-based model (ABM) where decision-making units, referred to as agents, represent individual farmers instead of a central planner. The model integrates three components: a biophysical agronomic model (DSSAT) for crop growth and development, an economic model for farmers' decision-making, and a groundwater model (MODFLOW) for water storage and movement in the aquifer and streams. We adopt a scenario-based approach, considering 32 climate scenarios based on 16 downscaled global climate models (GCMs) for two representative concentration pathways (RCPs), RCP4.5 and RCP8.5. Additionally, we evaluate three groundwater management policy instruments, namely irrigated land retirement, irrigation well retirement, and authorized pump rate reduction.

While this study is conducted on a regional scale, it contributes to understanding the sustainability of irrigated agriculture and groundwater resources in semi-arid regions worldwide amidst climate change. Specifically, the study: (1) underscores the indirect effects of climate change, including elevated CO₂, on groundwater systems; (2) illustrates the combined effects of groundwater depletion and climate change on crop production and farmers' profitability; and (3) evaluates the efficacy of various groundwater management policy instruments in conserving

groundwater and sustaining stream baseflows, as well as their impacts on agricultural and economic outcomes in the face of climate change.

5.2. Materials and Methods

In this section, we begin by providing background information on the area covered by the ABM-MODFLOW domain. We then explore the core features of ABM-MODFLOW's structure, with comprehensive details available in Chapter 4. Subsequently, we discuss climate projections and the methods used in the downscaling of GCMs. We conclude by presenting groundwater management scenarios examined in this study.

5.2.1. Study Area

The High Plains Aquifer (HPA), also known as the Ogallala Aquifer, is the primary source of irrigation water in the U.S. High Plains region, which accounts for over 11% of the U.S. total agricultural market value (Figure 5.1a; Scanlon et al., 2012). The HPA faces the highest groundwater depletion rate among major aquifer systems in the U.S. (Konikow, 2015). The ABM-MODFLOW domain covers a portion of the HPA in eastern Colorado and northwest Kansas, spanning parts of the Republican River and Smoky Hill River basins (Figure 5.1a).

Covering 20,928 km², the ABM-MODFLOW domain encompasses 200,118 ha of lands irrigated by 3,468 wells in 2018 (Figure 5.1b). Corn and winter wheat are the dominant crops, covering 62% and 16% of the groundwater-irrigated area on average between 2008 and 2017, respectively. Figure 5.1c highlights the heterogeneity among farmers in terms of well numbers and farm size, details that are accounted for in this study. Surface water irrigates less than 1% of irrigated lands, and the Bonny Reservoir is the region's sole reservoir primarily for flood control. In this semi-arid region, receiving an average annual rainfall of 435 mm and with a strong reliance

on groundwater, irrigated crop production has resulted in notable groundwater depletion since 1960. From 1960 to 2018, the region depleted 27.004 km³ of groundwater, at an average rate of 0.459 km³/yr. For context, the depletion volume is nearly the full capacity of Lake Mead, which holds 32.236 km³. During this period, 52% of the region experienced a decline of 25% or more in its saturated thickness; i.e., the vertical distance between the water table and bedrock.

Groundwater discharge to streams is vital for the water supply of aquatic ecosystems in the region (Zipper et al., 2021). However, intensive groundwater extraction captures the discharge, leading to significant baseflow reductions in the Republican River Basin. Specifically, there was a 98% and 94% decrease in the moving average annual baseflows from 1960 to 2018 for the Arikaree River and South Fork Republican River outlets, respectively. This situation sparked a number of litigations among Colorado, Kansas, and Nebraska, resulting in several settlements and agreements (Republican River Compact Administration, 2019). Following a settlement in 2002, Colorado drained the Bonny Reservoir by 2012. Since then, it has remained empty and is operated as a pass-through system, with the dam gates kept open (Bureau of Reclamation, 2018).

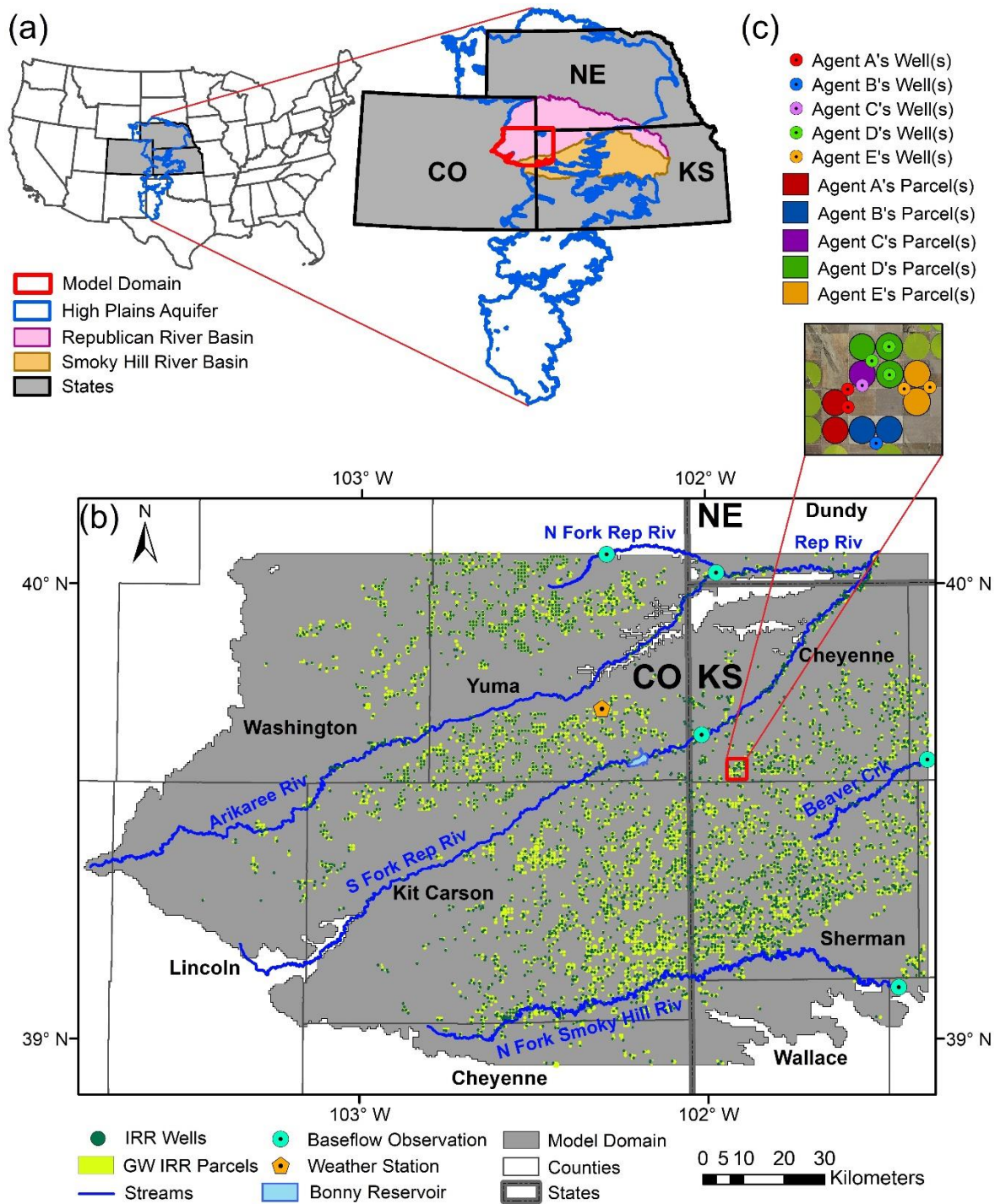


Figure 5.1. (a) Study area in relation to the High Plains Aquifer and major river basins. (b) ABM-MODFLOW domain with irrigated (IRR) wells and groundwater-irrigated (GW IRR) parcels in 2018. (c) Heterogeneity among farmers (agents) in terms of well numbers and farm size.

5.2.2. ABM-MODFLOW

The ABM-MODFLOW comprises an agronomic model (DSSAT), an economic model, and a groundwater model (MODFLOW), integrated through a set of Python post-processing scripts and a Windows batch script. The agronomic component employs the CERES-Maize and CERES-Wheat models from the Decision Support System for Agro-Technology Transfer version 4.7.5 (DSSAT; Hoogenboom et al., 2019; Jones et al., 2003). These biophysical crop models simulate the growth and development of dryland and irrigated corn (*Zea mays L.*) and winter wheat (*Triticum aestivum L.*) under different soil, management, and climate conditions. Cultivar coefficients for corn and winter wheat (Table C1 in the Appendix C) are specified as the calibrated values estimated based on experimental field data from farms near the study area (DeJonge et al., 2011; Elsayed et al., 2019). The crop simulations are conducted for 15 prevalent soil types identified in groundwater-irrigated parcels using the Soil Survey Geographic Database (SSURGO; Natural Resources Conservation Service, 2019). Table C2 in the Appendix C lists the soil types and their properties.

DSSAT enables the simulation of various irrigation management strategies through a number of parameters that influence the amount, timing, and duration of irrigation. In this study, we conduct DSSAT simulations for irrigated crops using a combination of six distinct critical plant available water (PAW_c) and 24 irrigation frequency (IFREQ) values, while keeping other parameters constant. PAW_c , which is expressed as a percentage of available water capacity (AWC), sets the soil moisture target and determines when irrigation is initiated; i.e., the higher the PAW_c , the more frequently irrigation is triggered. AWC represents the maximum water the soil can hold for plant uptake. IFREQ establishes the minimum interval between consecutive irrigation events

(Kisekka et al., 2018), reflecting the minimum time needed to irrigate the entire irrigated area during each event. It is calculated as follows:

$$\text{IFREQ} = \frac{\text{Irrigated Area} \times \text{Irrigation Application Depth}}{\text{Maximum Pump Rate}} \quad (5.1)$$

As irrigation application depth is consistently set at 25 mm, IFREQ changes with variations in the irrigated area and the maximum pump rate. When the maximum pump rate diminishes due to groundwater depletion and/or policies and the irrigated area remains unchanged, IFREQ increases. This leads to crops enduring extended periods without irrigation, potentially resulting in elevated water stress and reduced yields. The interplay between irrigated area and IFREQ presents a trade-off, where expanding the irrigated area comes at the expense of higher IFREQ, which in turn could reduce crop yield per unit area. Table C3 in the Appendix C provides the management parameters designated for corn and winter wheat in the DSSAT simulations.

Crop simulations use daily weather inputs from 2019 to 2099, provided by a given climate projection. These inputs are projected for the location of a weather station in Idalia, Colorado (Figure 5.1b). We selected this specific location for consistency, as the weather data recorded at this station were previously utilized for historical simulations and model validation (Chapter 4). Alongside daily weather data, we also incorporate annual CO₂ projections for RCP4.5 and RCP8.5 scenarios into the crop models (Figure C1 in the Appendix C). Considering various combinations of soil types and irrigation strategies, we obtain 2,160 crop production scenarios for each irrigated crop under every climate projection (15 soils × 6 PAW_cs × 24 IFREQs) and 15 scenarios for each dryland crop (15 soils). The derived crop yields and seasonal irrigation use from these simulations are compiled in a production outcome library for the economic model's application.

The economic model, developed in the R programming language, represents profit-maximizing agents and aims to identify the optimal planting and irrigation decisions for each agent. An agent is characterized as a collection of parcels coupled with the irrigation wells that serve them (Figure 5.1c). Key attributes unique to each agent, as required by the economic model, include the total farm area, the farm's dominant soil type, and the authorized pump rate and capacity of their irrigation wells. Well capacity, or well yield, is defined as the maximum rate of groundwater extraction from a well without causing it to run dry. The total farm area determines the number of farm management units available to each agent, which is equivalent to a 13.15 ha (32.5 ac) land parcel. Figure C2 in the Appendix C presents maps displaying various attributes of agents at the beginning of simulations. These attributes include the *AWC* of the dominant soil type, well capacities, and irrigation capacities, with the latter defined as the ratio of the combined capacity of irrigation wells to the total farm area. It is worth noting that we disregard variability among agents in terms of climate conditions, since DSSAT simulations are conducted using climate projections for a single location.

In the economic model, agents' decision-making follows a two-step approach, as illustrated in Figure 5.2. It is premised on the assumption that all agents act myopically; i.e., they focus on maximizing their expected profit for the upcoming growing season without considering potential profit increases in later seasons. In the first step, marking the beginning of the growing season, agents determine their planting and irrigation strategies based on both the policies in place and their individual attributes, while having no complete foresight about the weather conditions for the upcoming season. To account for this uncertainty, agents consider the distribution of climate outcomes in different years under a given climate projection, assigning equal weight to each year. However, due to the non-stationarity associated with climate change, this distribution gets updated

every 27 years. Therefore, climate projections are divided into short-term (2019-2045), mid-term (2046-2072), and long-term periods (2073-2099).

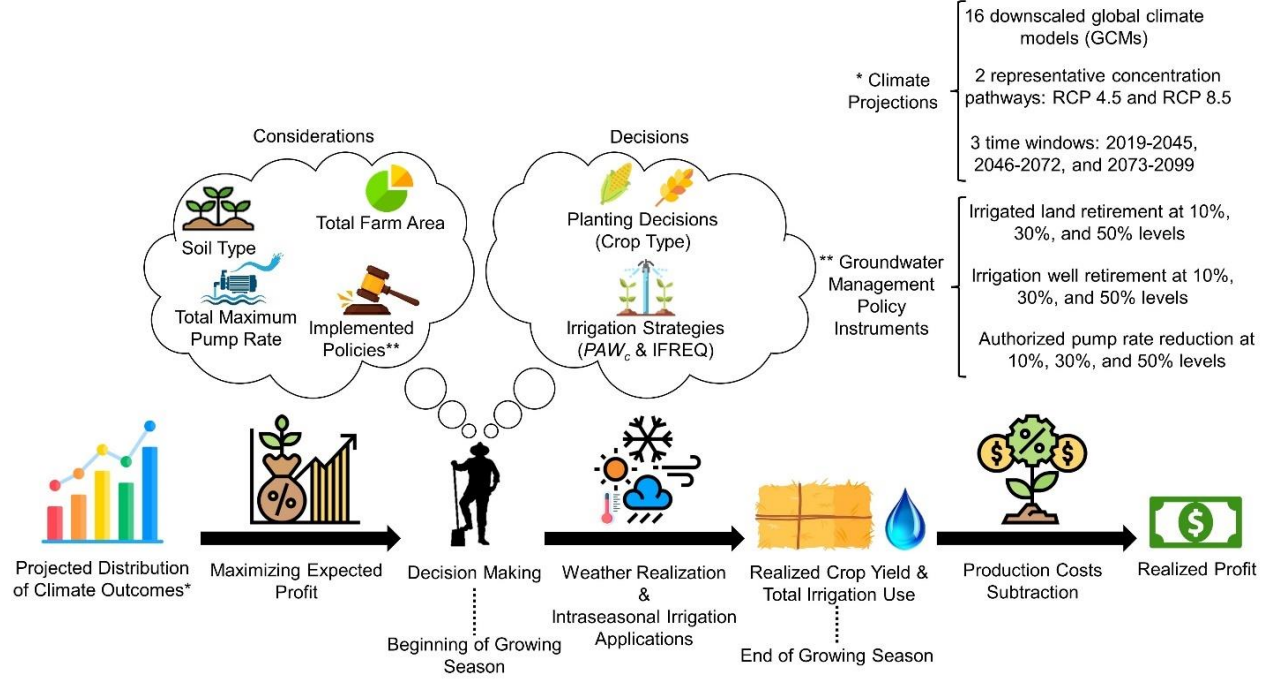


Figure 5.2. Representation of the agents' decision-making process within the economic model. PAW_c and IFREQ denote critical plant available water and irrigation frequency, respectively.

At the start of each growing season, a representative risk-neutral agent seeks to maximize their expected profit by determining the total area to be planted with irrigated crop n and the corresponding PAW_c value, as well as the total area for dryland crop m , as shown by the following equation:

$$\begin{aligned}
& \max E(\pi) \\
& = \max_{A_n, PAW_{cn}, A_m} E_{weather} \left\{ \sum_{n=1}^N A_n [p_n f_n(w_n(PAW_{cn}, \text{IFREQ}(\sum_{n=1}^N A_n, \bar{Q}), \text{weather}), \text{weather}, \text{soil}) \right. \\
& \quad \left. - w_n c - h_n] + \sum_{m=1}^M A_m [p_m f_m(\text{weather}, \text{soil}) - h_m] \right\}
\end{aligned} \tag{5.2}$$

subject to:

$$\bar{A} = \sum_{n=1}^N A_n + \sum_{m=1}^M A_m \tag{5.3}$$

$$\sum_{n=1}^N A_n \leq \left(1 - \frac{\alpha}{100}\right) \bar{A} \tag{5.4}$$

$$\bar{Q} = \sum_{i=1}^I \min(Q_i^{capacity}, (1 - \frac{\beta}{100}) Q_i^{authorized}) \tag{5.5}$$

where A_n and A_m represent the total area to be planted with irrigated crop n and dryland crop m , respectively. These areas are calculated by multiplying the number of farm management units dedicated to each crop by 13.15 ha (32.5 ac). PAW_{cn} is the PAW_c value selected for irrigated crop n . p_n and p_m denote the price of irrigated crop n and dryland crop m , respectively. The production function f_n generates the crop yield per unit land area for irrigated crop n in relation to the total irrigation per unit land area (w_n), seasonal weather realizations, and soil type. The value of w_n is derived from weather realization, PAW_{cn} , and IFREQ; the latter is dependent on the total area to be planted with irrigated crops and the total maximum pump rate ($\bar{Q}$), as outlined in Equation (5.1). $\bar{Q}$ is computed as the sum of the minimum values of well capacity ($Q_i^{capacity}$) and authorized pump rate ($Q_i^{authorized}$) for active irrigation wells, denoted by i . $Q_i^{authorized}$, which is specified in well permit and water right documents, is determined during the well's initial pump

test and represents the well capacity at the time of completion. $Q_i^{authorized}$ sets an institutional constraint on the maximum pump rate for well i , whereas $Q_i^{capacity}$ imposes a physical constraint. c represents the cost of pumping a unit volume of groundwater. The production function f_m computes the crop yield per unit land area for dryland crop m in relation to seasonal weather realizations and soil type. Lastly, h_n and h_m are the fixed production costs per unit land area for irrigated crop n and dryland crop m , respectively. We assume that p_n , p_m , c , h_n , and h_m remain constant throughout the simulation period. Table C4 in the Appendix C provides their values and details of their estimation.

Irrigated land retirement policies limit the total area that can be planted with irrigated crops by reducing irrigated lands to a specific percentage (α) of the total farm area ($\bar{A}$), as detailed in Equation (5.4). Both well retirement and authorized pump rate reduction policies affect $\bar{Q}$; the former deactivates a certain percentage of wells, while the latter reduces $Q_i^{authorized}$ by a specific percentage (β), as outlined in Equation (5.5). Under the no-action scenario, both α and β are set to zero, and all wells stay active unless they run dry.

After determining optimal planting and irrigation decisions in the first step, agents adhere to these decisions throughout the growing season. In the second step, as weather conditions in the growing season are realized, agents make irrigation application decisions with respect to daily variations of soil water content and their pre-season decisions. Once the growing season concludes, crop yields and total irrigation use for each agent are realized. From these values, the realized profit is computed by deducting the corresponding pumping and production costs from the total revenue.

To solve the optimization problem, the economic model leverages the production outcome library, which stores DSSAT simulation results, to pinpoint optimal crop choices and PAW_c values that maximize expected profit for different conditions of soil type, $\bar{Q}$, and $\bar{A}$. These optimal planting and irrigation decisions, along with the corresponding realized crop yield, seasonal irrigation use, and profit for each year, are compiled into a lookup table. Once the lookup table is established at the start of the simulation, it is consistently employed to determine the optimal decisions and resulting outcomes for each agent in every growing season. At the end of each season, simulated planted crops and seasonal irrigation use are passed to the post-processing scripts. These scripts calculate the average pumping rate for each irrigation well and the irrigation return recharge during the growing season based on irrigation use. Subsequently, these computed values are fed as inputs to the groundwater model. Additionally, planted crops are utilized to locate irrigated areas wherein the precipitation recharge is enhanced.

The groundwater model is developed using the MODFLOW-NWT model (Niswonger et al., 2011). This single-layer unconfined model is discretized horizontally with a uniform grid, consisting of 500 m $\times$ 500 m cells arranged in 252 rows and 420 columns. It has been calibrated and validated using measured data for groundwater levels and stream baseflows (Chapter 4). Every year, the MODFLOW model computes groundwater levels and stream baseflows on a daily time step, incorporating updated pumping and recharge values derived from the economic model outputs. We use the Python package FloPy (Bakker et al., 2016) to facilitate the updating of the MODFLOW model input files. In the MODFLOW model, each simulation year is divided into two stress periods with constant system stresses: a pumping period from May to September and a recovery period from October to April.

While the MODFLOW model has a single-layer structure, its hydrogeological parameters, namely effective horizontal hydraulic conductivity and effective specific yield, are updated at the start of each decade. First, we estimate these parameters for the upcoming decade in each borehole based on the trajectory of groundwater level variations from the preceding decade (Figure C3 in the Appendix C). The borehole-level values are then spatially interpolated to assign updated values to each model cell. In the MODFLOW model, annual precipitation recharge is estimated based on annual precipitation using power functions. To determine the annual precipitation in each model cell from 2019 to 2099, we sum up the daily precipitation in the cell provided by a given climate projection.

To minimize the potential impact of boundary conditions on the simulation outcomes, we assume the lateral flows in the eastern, northern, and southern boundaries of the MODFLOW model domain will stay constant throughout the simulation period. The specified flow rates for these boundary cells are determined by averaging the daily lateral flow rates in each cell from 2009 to 2018, as simulated by the MODFLOW model. Additionally, to estimate the maximum ET flux from the groundwater table, we take the average of the maximum ET flux specified for the MODFLOW model between 2009 and 2018. Despite potential increases in the maximum ET flux in the future due to climate change, its impact on the simulation results is expected to be minimal. This is because the groundwater level in 2018 was below the assumed rooting depth of 2 m for more than 99% of the region.

At the end of each simulation year, marked by April 30th, the computed groundwater levels are transferred to the post-processing scripts. Within these scripts, well capacities are updated in relation to variations in aquifer saturated thickness, using an empirical equation derived in Chapter 4:

$$Q_{it2}^{capacity} - Q_{it1}^{capacity} = 1.59 \frac{Q_{it1}^{capacity} (b_{t2} - b_{t1})}{b_{t1}} \quad (5.6)$$

where $Q_{it1}^{capacity}$ and $Q_{it2}^{capacity}$ denote the capacity of well i at times $t1$ and $t2$, respectively, while b_{t1} and b_{t2} represent the corresponding saturated thickness. Subsequently, a new $\bar{Q}$ is calculated for each agent using the updated well capacities (Equation (5.5)). These updated $\bar{Q}$ values are then used by the economic model to simulate the planting and irrigation decisions of agents for the upcoming growing season. This whole procedure is repeated for each growing season throughout the simulation period. Although this study primarily focuses on simulating the period from 2019 to 2099 (81 years) and analyzing the results for this timeframe, we initiate the simulations in 2018 using measured climate forcing data to mitigate the influence of initial conditions on our analysis.

5.2.3. Climate Projections

In this study, we conduct the ABM-MODFLOW simulations using 32 distinct climate scenarios. These scenarios originate from the downscaled climate projections of 16 GCMs in the Coupled Model Intercomparison Project Phase 5 (CMIP5; Taylor et al., 2012) for RCP4.5 and RCP 8.5. Following common practice, we incorporate multiple GCMs and RCPs into the simulations to account for uncertainties inherent in future climate and greenhouse gas emission projections (Ou et al., 2018). Table C5 in the Appendix C details the GCMs considered in this study, including their resolution and associated institution.

The GCMs are statistically downscaled through the Multivariate Adaptive Constructed Analogs (MACA) method (Abatzoglou and Brown, 2012), which involves multiple steps. Initially, quantile mapping is employed as a bias correction technique to align the mean and variance of

daily GCM data with daily historical observations from the gridMET (METDATA) dataset for the 1979-2012 period (Abatzoglou, 2013). This is followed by an epoch adjustment to eliminate the risk of lacking historical analogs for projected GCM data. Subsequently, a constructed analogs approach is used to identify the 30 best fine-scale spatial patterns from a library of observed patterns centered on a 45-day window for every calendar date. Linear combinations of these spatial patterns produce the downscaled GCM fields. For coherence, analog identifications are performed jointly for dew point, minimum, and maximum temperatures, while wind velocity and precipitation analogs are determined separately. Following a reintroduction of epoch adjustments, a final quantile mapping on the downscaled data ensures their statistical consistency with observations. The downscaled data for dew point temperature, along with minimum and maximum temperatures, are then used to calculate minimum and maximum relative humidity, which are then bias corrected based on observed data. The spatial resolution of downscaled data is determined by the gridMET resolution (training data), which is ~ 4 km (1/24th degree).

We obtained the primary MACA downscaled climate variables for each GCM from the Northwest Knowledge Network (University of Idaho, 2019). Following post-processing, we produced downscaled gridded climate variables required by the ABM-MODFLOW. These variables are: daily minimum and maximum temperature, daily total precipitation, daily average relative humidity, daily average downward solar radiation, and daily average wind speed at 2 m.

5.2.4. Management Scenarios

We evaluate three regulatory instruments for groundwater management in this study: irrigated land retirement, irrigation well retirement, and authorized pump rate reduction, which are implemented through a centralized governance approach, also referred to as command and control (Khan and Brown, 2019). In the irrigated land retirement instrument, a specific percentage of each

agent's farmland is removed from irrigated crop production, designating it for dryland crops. With irrigation well retirement, a certain percentage of all irrigation wells are randomly retired, causing varied outcomes for agents; some agents face direct impacts when their wells are retired, while others are indirectly affected if their neighboring wells are retired. The authorized pump rate reduction instrument decreases the authorized pump rate for each well by a specific percentage. Although this instrument intends to reduce the maximum pump rate for all wells by altering the institutional constraint, the actual impact varies among wells depending on well capacity, which is the physical constraint, as outlined in Equation (5.5).

These policy instruments are incorporated into the ABM-MODFLOW simulations from 2018 onwards, with implementation at three different levels: 10%, 30%, and 50%. For the well retirement instrument, as we move to higher levels, additional wells are randomly selected for retirement on top of those already retired at lower levels. Figure C4 in the Appendix C shows the retired wells in different policy levels.

We focus on these policy instruments because of their technical feasibility in both implementation and enforcement. For example, the maximum pump rate of a well can be effectively controlled by modifying its design, and satellite remote sensing can be employed to monitor irrigated areas (Deines et al., 2019; Foster et al., 2020). However, we do not account for the costs associated with the implementation and enforcement of these policies, including incentives paid to farmers to retire their irrigated lands or wells. Furthermore, we do not consider the political viability of these policies. For instance, based on existing policies in neighboring regions, implementing these policy instruments at the 50% or even 30% level might not be viable (Aistrup et al., 2017; Whittemore et al., 2023). It is essential to note that our primary objective is

not to formulate effective policies per se, but rather to explore the system dynamics in various climate and regulatory scenarios.

Besides the policy instruments previously mentioned, we include a no-action (status quo) scenario as the baseline. With this no-action scenario, the ABM-MODFLOW simulations encompass 10 management scenarios: one no-action, three for irrigated land retirement, three for irrigation well retirement, and three for authorized pump rate reduction. In the simulations, we do not consider the existing groundwater management policies in the study area, including a Local Enhancement Management Area (LEMA) program that covers the entire Groundwater Management District 4 in northwest Kansas and was initiated in 2018 (Whittemore et al., 2023).

To account for the impact of the opportunity cost of money on the value of future profits, we calculate the net present value (*NPV*) of profit from 2019 to 2099 for each management scenario. *NPV* represents the discounted sum of annual profits projected by the ABM-MODFLOW, with 2019 as the base year. It is calculated as follows:

$$NPV = \sum_{t=2019}^{2099} \frac{R_t}{(1+r)^{t-2019}} \quad (5.7)$$

where R_t denotes the profit in year t , and r represents the discount rate, which is assumed to be 5%.

To effectively explore the heterogeneous impacts of different policy instruments on the profitability of individual farmers, we develop an ordinary least squares (OLS) model. This model quantifies the change in *NPV* of each farmer's profit resulting from policy implementation, based on their distinct attributes:

$$\Delta NPV_a = \theta_0 + \theta_1 I_a + \theta_2 D_a + \theta_3 S_a + \gamma_j + \epsilon_a \quad (5.8)$$

where ΔNPV_a represents the change in NPV of profit per unit land area for farmer a under a given policy, relative to the no-action scenario. I_a denotes the irrigation capacity of farmer a in 2018, while D_a represents the number of active irrigation wells within a 3000-m radius of farmer a 's farm centroid in 2018, excluding any wells owned by farmer a . This search radius is selected based on the findings presented in Chapter 2. S_a denotes the AWC of the dominant soil type in farmer a 's farm. The term γ_j represents a fixed effect for groundwater management district j , included to account for potential unobserved heterogeneity among different administrative units, as suggested by Hrozencik et al. (2017). The θ values are the model's intercept and slope coefficients, and ϵ_a is a random error term with a mean of zero.

5.3. Results

In this section, we present the results of the ABM-MODFLOW simulations across 320 scenarios (16 GCMs $\times$ 2 RCPs $\times$ 10 policies). We start by exploring projected crop choices followed by an analysis of the factors driving shifts in crop selections. Next, we investigate temporal trends in region-wide profits and evaluate the effects of groundwater management policies on both aggregate and individual profits. We also present outputs related to the groundwater system, such as the time series of groundwater storage and stream baseflows, and highlight changes in the aquifer's saturated thickness resulting from the implementation of policies. Lastly, we conduct a comprehensive comparison of policy instruments, assessing their impacts on key system components, namely farmers' profit, groundwater storage, and stream baseflows.

5.3.1. Agronomic Outcomes

The distributions of the total area planted with each crop in 2032, 2059, and 2086, as projected by the ABM-MODFLOW under an ensemble of climate projections for RCP4.5, are illustrated in Figure 5.3. These distributions show evolving crop preferences across different management scenarios. Across these scenarios, we observe a consistent decline in areas planted with irrigated and dryland corn. Conversely, irrigated winter wheat shows an increasing trend. In 2086, virtually no land is dedicated to dryland corn across all management scenarios. However, the area planted with dryland winter wheat remains relatively stable over time under all management scenarios. The pronounced variability in the planted area of irrigated corn and irrigated winter wheat in 2059 suggests a transition from irrigated corn to irrigated winter wheat during the mid-term projection period.

Irrigated corn is the dominant crop in 2032 across all management scenarios, with the exception of the 50% well retirement policy (Figure 5.3). Most policies, in comparison to the no-action scenario, lead to a significant reduction in areas cultivated with irrigated corn in 2032. However, the 30% and 50% land retirement policies indicate an increased preference for irrigated corn in 2059 and 2086 compared to the baseline. This is because of sustained well capacity, allowing farmers to grow this water-intensive crop in later years.

In 2059 and 2086, irrigated winter wheat becomes the dominant crop under all management scenarios, with the exception of the 50% land and well retirement policies (Figure 5.3). Compared to the no-action scenario, both the land retirement and well retirement policy instruments significantly decrease the area under irrigated winter wheat in 2059 and 2086. In contrast, the 50% authorized pump rate reduction policy induces a marginal increase. This is because, under the pump rate reduction policy, groundwater conservation is achieved without removing any parcel or

well from irrigated crop production. Thus, with conserved groundwater and limited maximum pump rates, farmers increasingly favor irrigated winter wheat, which is less water-intensive than corn.

Regarding dryland winter wheat, the areas under cultivation expand notably relative to the baseline under both the land retirement and well retirement policy instruments in all three years (Figure 5.3). Specifically, dryland winter wheat becomes the dominant crop in 2059 and 2086 under the 50% land retirement policy; it is also the prevalent choice in 2032 and 2059 under the 50% well retirement policy.

For the RCP8.5 projections, relative to RCP4.5, there is a diminished preference for both irrigated and dryland corn across all management scenarios, while irrigated winter wheat sees an increased preference (Figure 5.4). Notably, in 2059 and 2086, virtually no area is planted with irrigated and dryland corn across all climate projections and management scenarios. In 2032, while irrigated corn remains the primary choice for most management scenarios, dryland winter wheat is the preferred choice under the 50% land and well retirement policies. In 2059 and 2086, irrigated winter wheat either is the top choice or shares the top place with dryland winter wheat across all management scenarios. The high variability in the area planted with irrigated corn and irrigated winter wheat in 2032 is indicative of a shift from irrigated corn to irrigated winter wheat during the short-term projection period for RCP8.5.

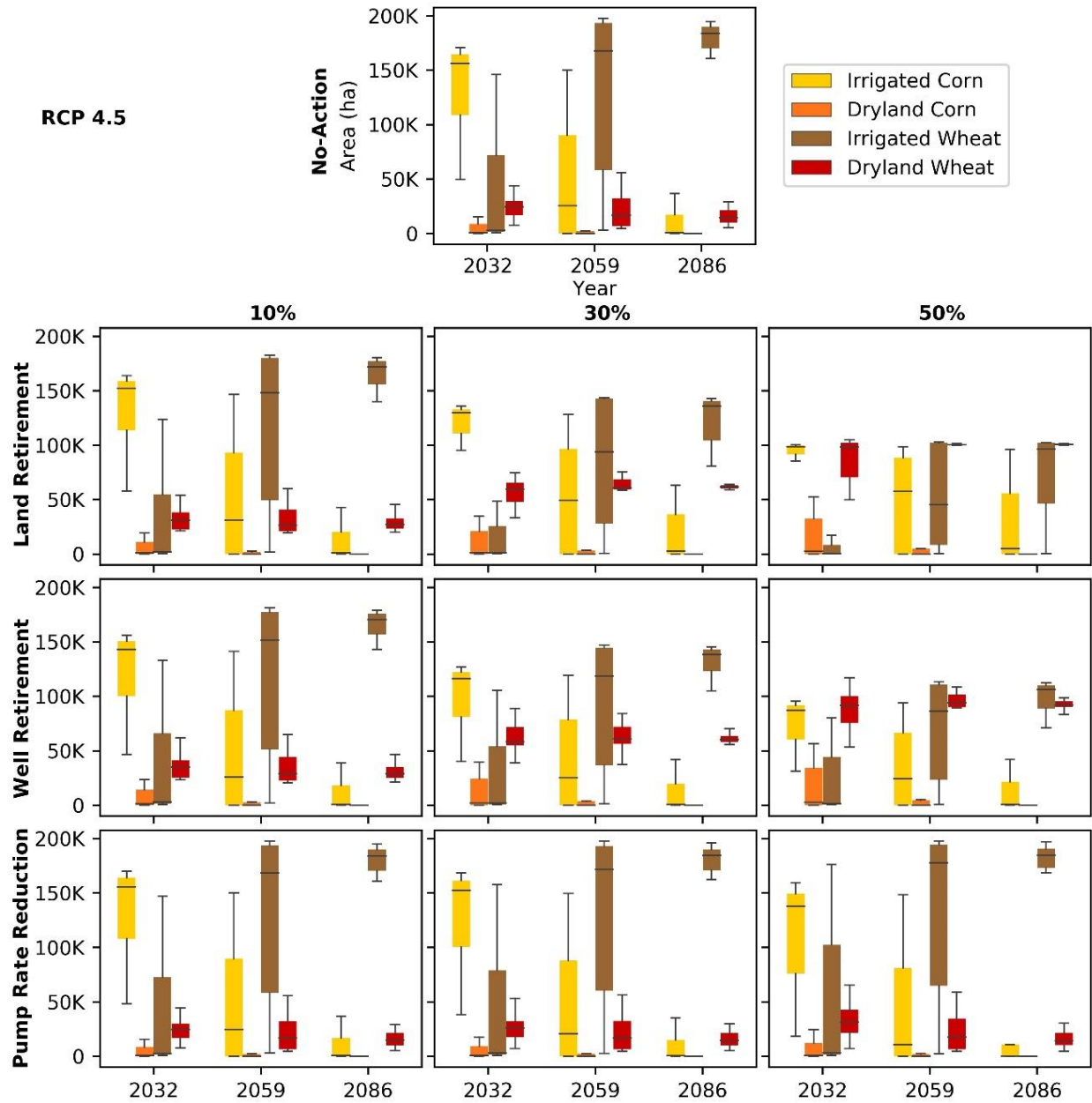


Figure 5.3. Distributions of the total area planted for each crop in 2032, 2059, and 2086, as projected by the ABM-MODFLOW under an ensemble of climate projections for RCP4.5 and different management scenarios. These three years are the median years of short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).

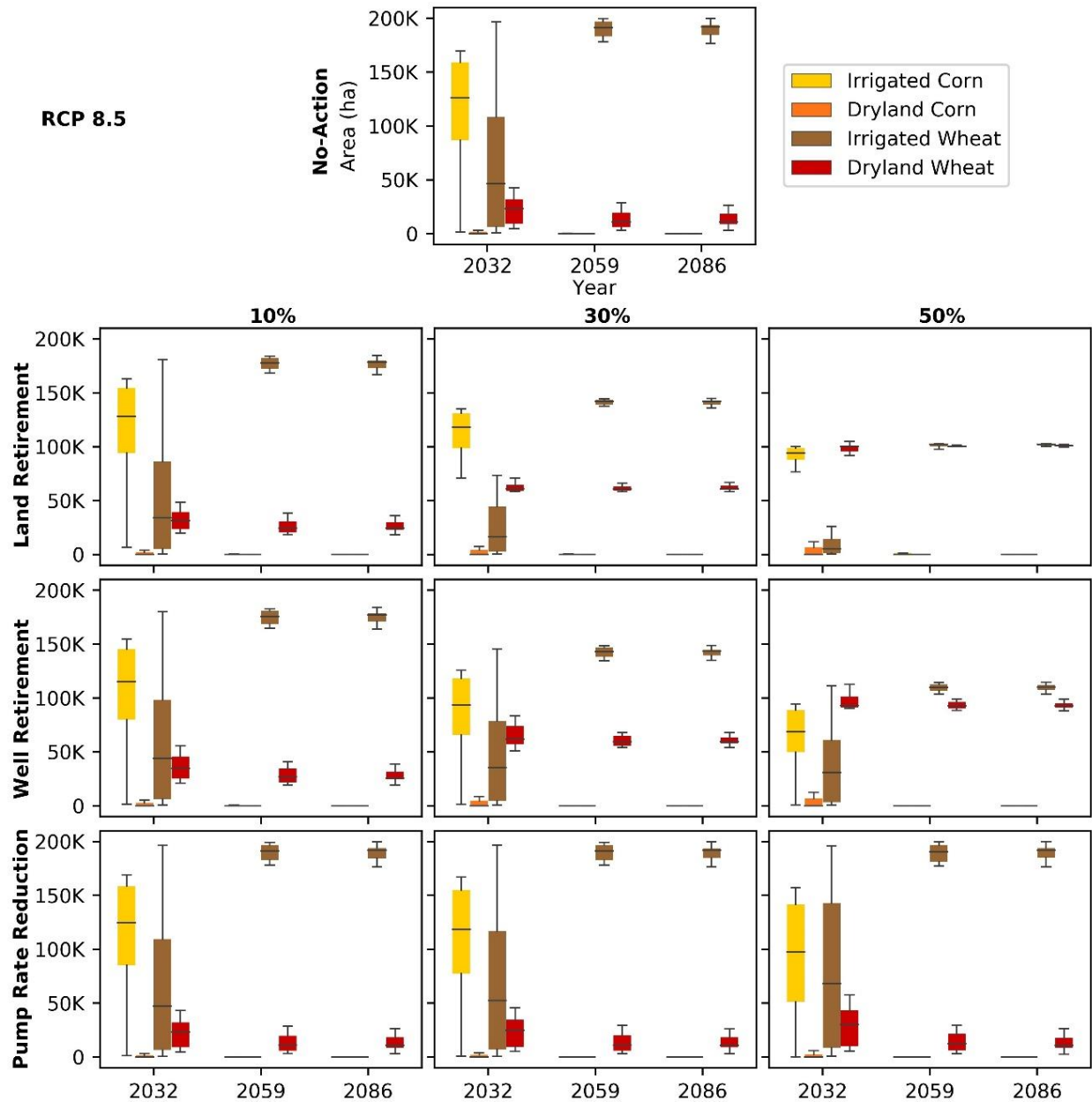


Figure 5.4. Distributions of the total area planted for each crop in 2032, 2059, and 2086, as projected by the ABM-MODFLOW under an ensemble of climate projections for RCP8.5 and different management scenarios. These three years are the median years of short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).

Figures C5 to C24 in the Appendix C display the percentages of selected crops on farms across the study area for the years 2032, 2059, and 2086. Based on these figures, it is typically the farmers with lower initial irrigation capacities and/or lower soil AWC values (Figures C2a and C2c

in the Appendix C) who initiate the transition from irrigated corn to irrigated winter wheat. This trend is particularly evident in western Yuma, Kit Carson, and southwest Sherman counties. The impact of soil *AWC* is more pronounced under RCP8.5. It is important to note that implementing policies at high levels significantly alters these spatial patterns.

To explore the factors behind the shifts in crop choices projected by the ABM-MODFLOW, we evaluate crop yields simulated by the agronomic model (DSSAT) for the 2019-2099 period (Figure 5.5). Crop yields are averaged over all soil types included in the ABM-MODFLOW simulations. For irrigated crops, we set PAW_c and IFREQ values at 55% and 3, respectively, representative of full irrigation conditions. Our analysis omits the effects of groundwater availability, isolating the impact of climatic factors on crop yields. We observe a decreasing trend in yields for both irrigated and dryland corn over the entire simulation period, whereas irrigated and dryland winter wheat yields exhibit an increasing trend. Both trends are more pronounced under RCP8.5. These results are consistent with the outcomes of previous crop modeling efforts within the region and at the global scale (Elsayed et al., 2019; Jägermeyr et al., 2021).

The decline in corn yields can be largely attributed to rising summer temperatures, especially during crucial growth stages like flowering (anthesis). In the study area, corn flowering typically occurs in July, and the optimal temperature for this stage is 25 °C (Lizaso et al., 2018). From the initial years of the simulation period, the average daily mean temperature in July exceeds the optimal temperature in many climate projections under RCP4.5, and even more so under RCP8.5 (Figure 5.5). In contrast, winter wheat flowering, which usually takes place in May, is not adversely affected by temperature increases. The average daily mean temperatures for May stay below the optimal temperature for wheat flowering, identified as 21 °C (Jacott and Boden, 2020;

John and Megan, 1999), in the majority of climate projections through to the end of the century. Furthermore, while newer winter wheat varieties are bred to mature earlier and thus avoid the peak high temperatures of summer, they are more vulnerable to spring freezes (Rogers, 1997). Therefore, winter wheat is likely to benefit from the rising temperatures in spring.

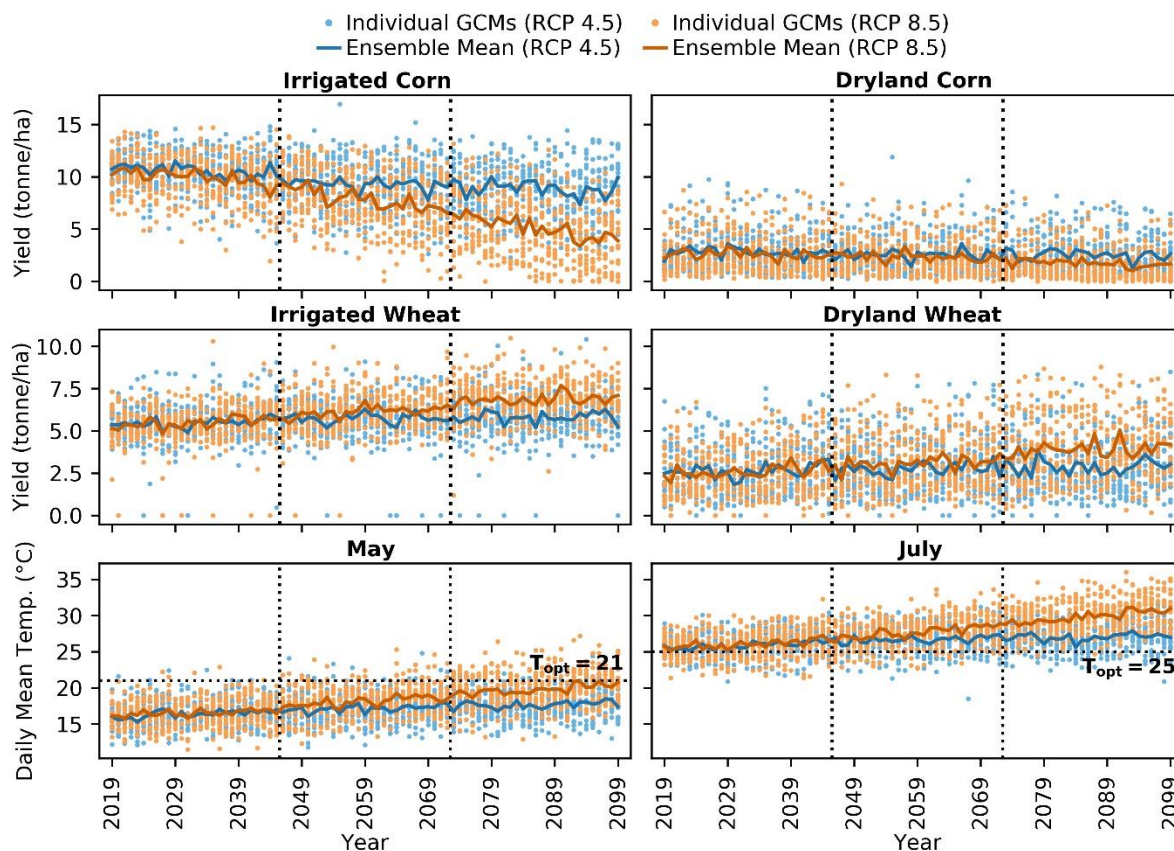


Figure 5.5. Simulated crop yields using the agronomic model (DSSAT) based on climate projections from an ensemble of global climate models (GCMs) for RCP4.5 and RCP8.5 (top and middle panels). Average daily mean temperature in May (winter wheat flowering stage) and July (corn flowering stage) derived from these GCM projections for the same RCPs (bottom panel). Vertical dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099). Horizontal dotted lines indicate the optimal temperatures (T_{opt}) for winter wheat and corn flowering.

Besides rising temperatures, this study also considers the effects of elevated CO₂ levels on crop yields. Increased CO₂ is expected to enhance photosynthesis as well as reduce stomatal conductance and transpiration, leading to greater crop light utilization and water productivity

(Ahmed et al., 2019; Deryng et al., 2016). However, the response to elevated CO₂ levels varies among crops; corn, which has a C₄ photosynthetic pathway, shows a limited response, whereas wheat, a C₃ crop, exhibits a stronger response, leading to sizable increases in growth and yield (Kimball, 2016; Tausz et al., 2013). Considering the detrimental impact of rising temperatures on corn yields, alongside the beneficial effects of elevated CO₂ levels on winter wheat, it is anticipated that both irrigated and dryland corn will become less profitable in the region. Conversely, both irrigated and dryland winter wheat are projected to increase in profitability as the century progresses, prompting farmers to shift their production from corn to winter wheat.

Figures C25 to C32 in the Appendix C display time series of region-wide crop production as projected by the ABM-MODFLOW. The 30% and 50% land retirement and well retirement policies result in a slight increase in dryland corn production in the short-term. However, this production plummets to nearly zero in the mid and long-term due to rising temperatures. Under all management scenarios, irrigated corn production has a declining trend in the short-term and diminishes significantly in the subsequent periods due to rising temperatures. Although the majority of policies initially reduce irrigated corn production, they temper its decreasing trend, as the dominant factor becomes rising temperatures rather than groundwater depletion. Notably, under RCP4.5, the mid and long-term projections for irrigated corn production show a modest increase with the 30% and 50% land retirement policies. For dryland winter wheat, there is a significant increase in production with the introduction of land retirement and well retirement policies. Throughout the simulation period, dryland winter wheat production has a rising trend across all management scenarios. This positive trend is due to the favorable conditions for winter wheat stemming from climate change. On the other hand, irrigated winter wheat production decreases with the land retirement and well retirement policies, but it sees a slight rise under the

50% authorized pump rate reduction policy. This increase is attributed to the expansion of areas planted with irrigated winter wheat. Like its dryland counterpart, irrigated winter wheat production exhibits an increasing trend throughout the simulation period.

5.3.2. Economic Outcomes

A time series analysis of region-wide undiscounted annual profit per unit land area, as projected by the ABM-MODFLOW, reveals the temporal patterns in profitability under different management conditions (Figures 5.6 and 5.7). To assess the significance of these trends during each projection period, we employ the Mann-Kendall test (Mann, 1945). For estimating the trend slopes, Sen's slope estimator is applied (Sen, 1968). Under RCP4.5, despite annual fluctuations, the no-action scenario exhibits an L-shaped trend in profits, characterized by a decreasing trend in the short-term, which then transitions to a phase of stabilization over the mid and long-term (Figure 5.6). The short-term negative trend can be attributed to rising temperatures and reduced well capacity, both affecting irrigated corn. In the subsequent periods, annual profits stabilize primarily because temperatures rise to levels that limit irrigated corn production, prompting a shift toward irrigated winter wheat as the dominant crop. The rising trend in winter wheat yields, driven by climate change, mitigates the negative effects of reduced well capacity on irrigated winter wheat production.

Under RCP8.5, the no-action scenario shows a U-shaped trend in annual profits, with a declining trend in the short-term, followed by stagnation in the mid-term, and leading to an increasing trend in the long-term (Figure 5.7). The initial declining trend is smaller than that observed under RCP4.5, which is attributed to a reduction in the area planted with irrigated corn in response to higher temperatures, accompanied by a more significant increase in winter wheat yields. The increasing yields of winter wheat offset the negative impacts of diminished well

capacity on irrigated winter wheat production, contributing to the upward trend in long-term annual profits.

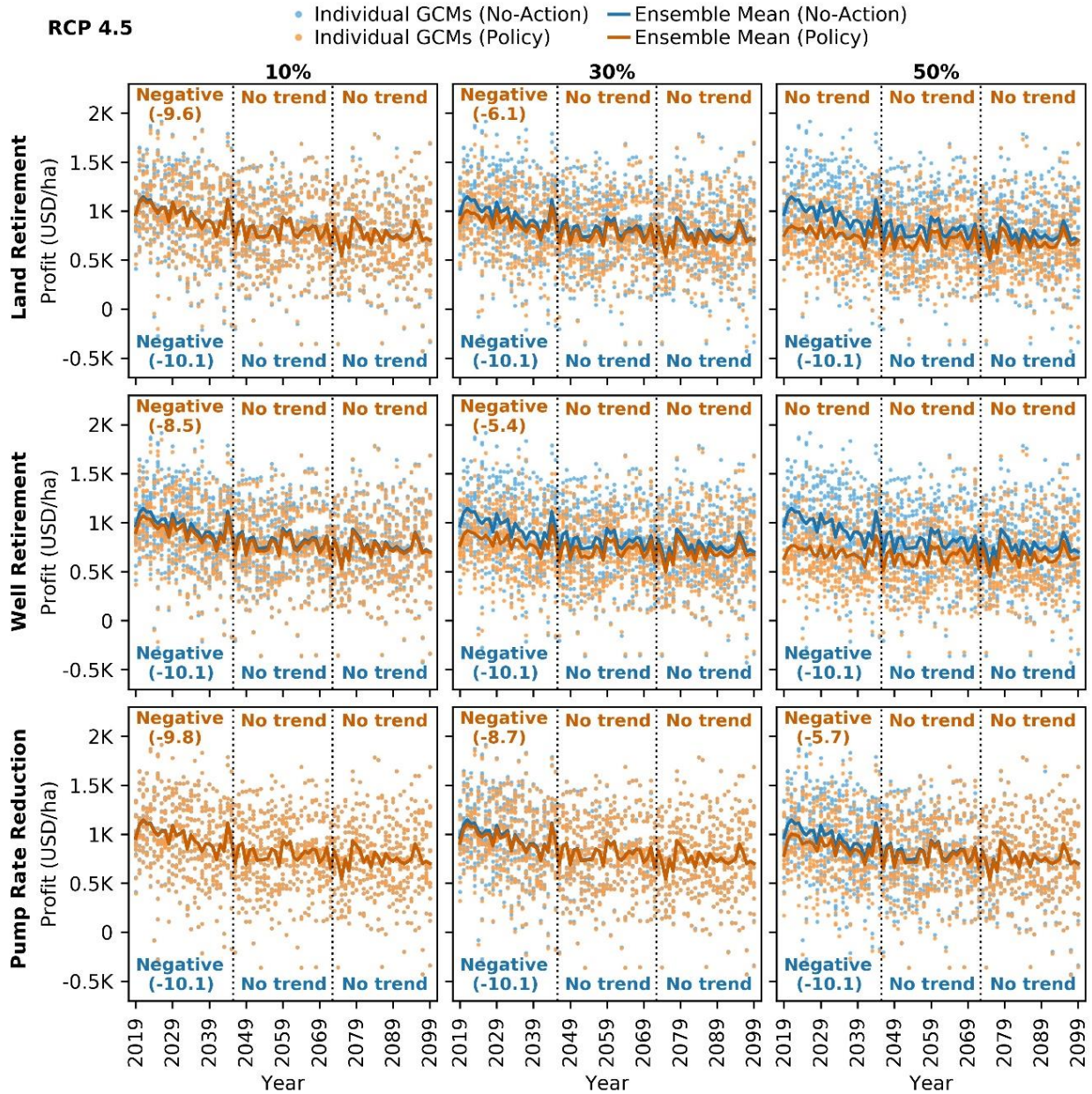


Figure 5.6. Region-wide undiscounted annual profits per unit land area as simulated by the ABM-MODFLOW, based on an ensemble of global climate models (GCMs) projections for RCP4.5 under various management scenarios. Annotations within the plots present the Mann-Kendall test results for trend significance, and numbers in parentheses indicate the Sen's slope estimator values for trend slopes, where significant. Blue annotations correspond to the no-action scenario, while orange annotations pertain to scenarios with policy interventions. Dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).

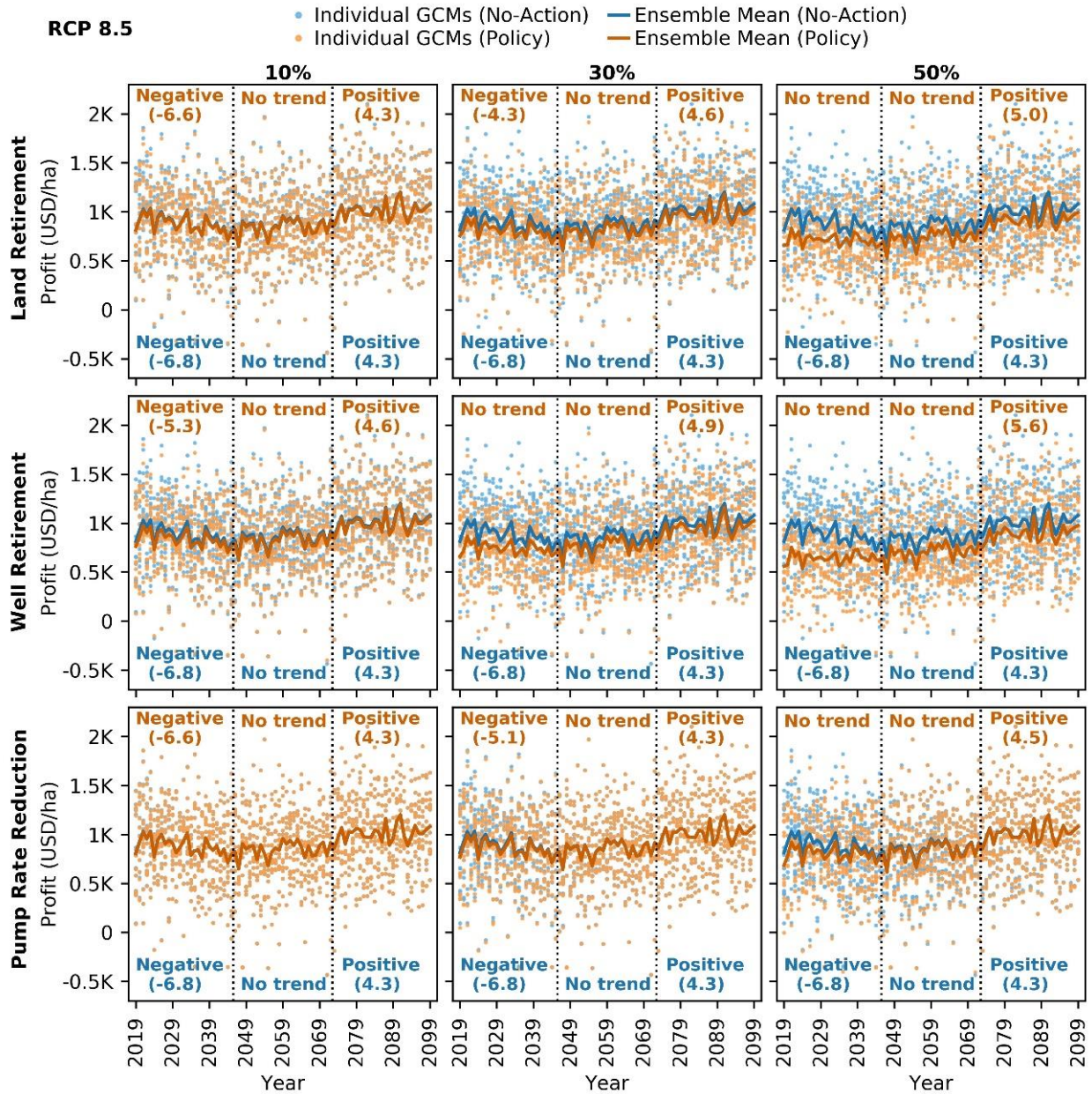


Figure 5.7. Region-wide undiscounted annual profits per unit land area as simulated by the ABM-MODFLOW, based on an ensemble of global climate models (GCMs) projections for RCP8.5 under various management scenarios. Annotations within the plots present the Mann-Kendall test results for trend significance, and numbers in parentheses indicate the Sen's slope estimator values for trend slopes, where significant. Blue annotations correspond to the no-action scenario, while orange annotations pertain to scenarios with policy interventions. Dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).

Under both RCPs, the implementation of groundwater management policies results in an initial drop in profits, reflecting the costs associated with reduced water usage. However, these policies moderate the initial declining trend in annual profits and, in some cases, even stabilize it by reducing the area planted with water-intensive irrigated corn, which is replaced with either dryland or irrigated winter wheat. Thus, fewer parcels are subject to the negative effects of increasing temperatures and well capacity constraints, while more parcels benefit from the rising yields of winter wheat. Under RCP8.5, the pronounced upward trend in long-term profits with the 50% land and well retirement policies is attributed to an expanded cultivation of dryland winter wheat compared to the baseline scenario. This crop benefits from increasing yields over time without being affected by reduced well capacity.

The annual profits under the no-action scenario and those under policy interventions tend to converge over the long term for both RCPs, across all policy instruments. This convergence is driven by a transition from corn to winter wheat in response to rising temperatures, along with sustained well capacity due to policies, which improves yields for irrigated corn and winter wheat in later decades. However, profits under policy interventions never exceed the baseline profits because the groundwater conserved in the early years is primarily used for winter wheat irrigation later on, which has a considerably lower irrigation value than corn (Smidt et al., 2016). Considering this, and the fact that these profits are not discounted for the time value of money, it becomes clear that climate change undermines the efficacy of groundwater management policies by restricting the production of irrigated corn in the future.

Apart from assessing region-wide profits, we also evaluate the impacts of policies on individual farmers' profitability. This is done by comparing the farmer-level *NPV* of profit from 2019 to 2099 (Equation (5.7)) under each policy scenario with that of the no-action scenario. To

facilitate the comparison, we compute the farmer-level *NPV* as the ensemble mean, averaging across the simulation outcomes derived from multiple GCM projections for each RCP. Figure 5.8a presents the *NPV* of profit per unit land area for individual farmers across the study area under the no-action scenario for RCP4.5. Farmers with higher initial irrigation capacities (Figure C2c in the Appendix C) tend to have the highest *NPVs*, and their farms are generally located on the thick pockets of the aquifer (see Figure C33 in the Appendix C for the aquifer's saturated thickness in 2018).

The maps displaying the percent change in *NPV* of profit, relative to the baseline, under different policies for RCP4.5 highlight the impact of these policies on the profitability of individual farmers (Figure 5.8b). Under land retirement policies, it is generally observed that farmers with lower profitability benefit from these policies, while those with higher profitability often experience a decrease in *NPV*. However, these spatial patterns vary under different levels of policy implementation. The spatial distribution of percent change in *NPV* under well retirement policies is highly dependent on the locations of the retired wells. Compared to other policy instruments, well retirement leads to extreme changes in *NPV*; i.e., some farmers experience significant benefits, while others face substantial declines. However, under the 10% and 30% well retirement policies, the majority of farmers experience an increase in *NPV*. Similar to land retirement policies, authorized pump rate reduction policies tend to negatively affect farmers with higher profitability, while those with lower profitability may see benefits.

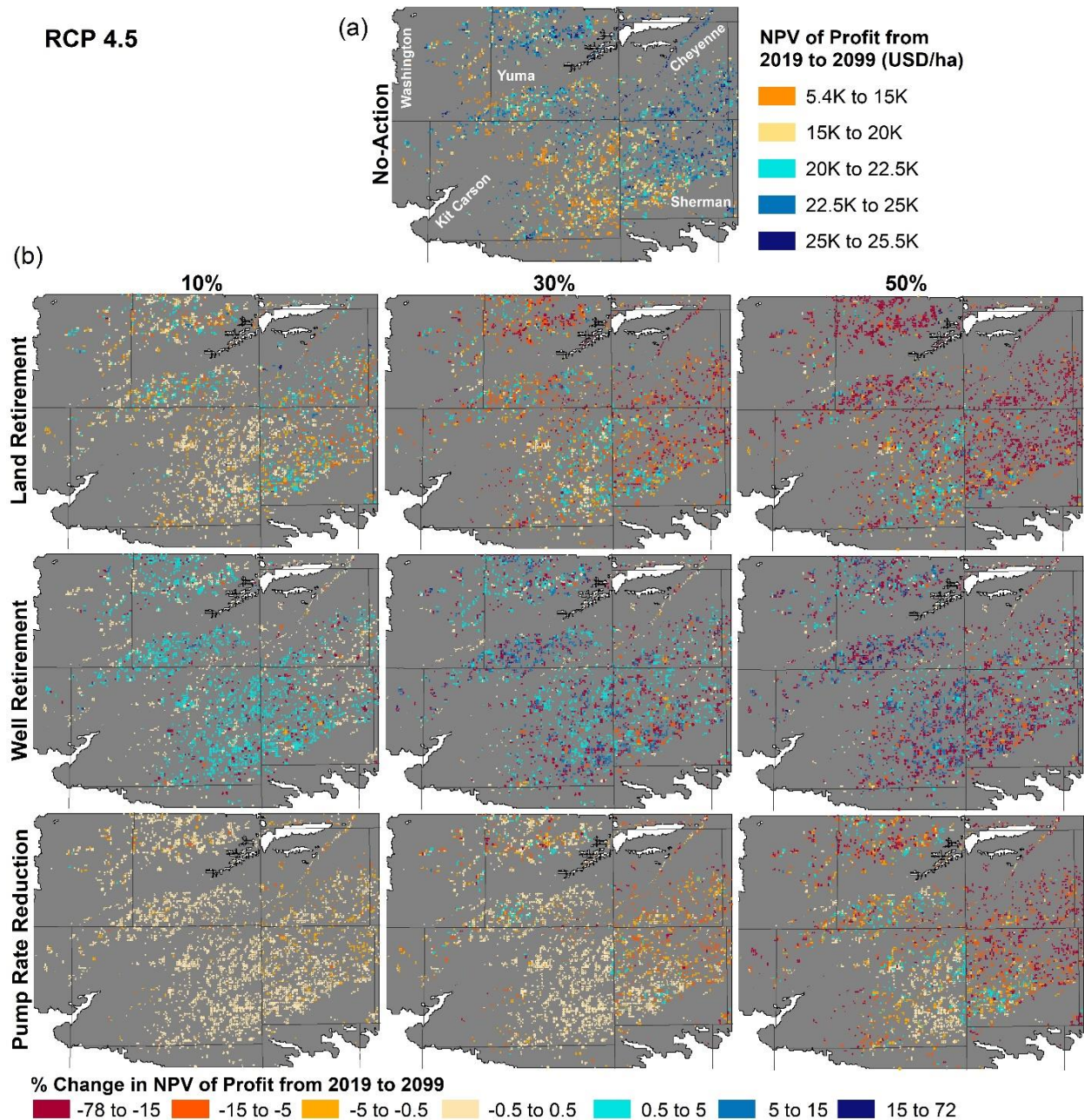


Figure 5.8. Influence of groundwater management policies on farmers' profitability across the region under RCP4.5. (a) Net present value (*NPV*) of profit per unit land area for individual farmers under the no-action scenario, with *NPV* calculated as the ensemble mean of simulation outcomes under climate projections from multiple global climate models (GCMs). (b) Percent change in *NPV* of profit, relative to the no-action scenario, under different groundwater management policies.

The spatial distribution of the *NPV* of profit per unit land area under the no-action scenario for RCP8.5 is similar to RCP4.5, except that farmers with higher initial irrigation capacities have lower *NPVs* (Figure C34a in the Appendix C). These lower *NPVs* are attributed to the detrimental effects of rising temperatures under RCP8.5 on irrigated corn production in the region. In terms of policy impacts on *NPV* under RCP8.5, while spatial patterns are consistent with RCP4.5, the percent changes in *NPV* under land retirement and well retirement policy instruments are less pronounced (Figure C34b in the Appendix C). This results in a moderation of both positive and negative effects on farmers' profitability.

Figures C35 and C36 in the Appendix C display the distribution of the percent change in farmers' *NPV* of profit, relative to the baseline, under various policies for each RCP. The variability in the percent change of *NPV* increases with the implementation of policy instruments at higher intensities. This variability is more pronounced for well retirement policies than for the other two policy instruments. While the majority of farmers see an increase in *NPV* under the 30% well retirement policy, the distribution of percent change in *NPV* is negatively skewed, indicating that a subset of farmers experience considerably large declines in *NPV*. Under RCP8.5, the variability in the percent change of *NPV* slightly decreases for all policy scenarios, except when policies are implemented at a 10% level, which appear to have a negligible impact on farmers' *NPV*.

To better explore the heterogeneous impacts of different policy instruments on individual farmers' profitability, we develop an OLS model, as outlined in Equation (5.8). We subsequently estimate the intercept and slope coefficients for each policy scenario, with the results provided in Table 1. The results indicate that land retirement policies generally lead to more negative profit outcomes for farmers with larger initial irrigation capacities and for those with soils that have a

higher AWC. This supports the notion that farmers with initially higher profitability face greater losses under these policies, as they are required to cease irrigation on a portion of their farm despite having soils with high water-holding capacity and ample irrigation capacity. In contrast, farmers in areas with a higher well density tend to benefit more from land retirement policies.

Under well retirement policies, farmers with no retired wells exhibit a negative correlation between initial irrigation capacities and the policies' impact on profits, suggesting that those with lower initial capacities typically benefit more from the groundwater conserved through the retirement of neighboring wells. Moreover, among this group, farmers in areas with a higher density of wells and those with soils of higher AWC generally benefit more from well retirement policies. However, soil AWC does not significantly affect profit outcomes under the 50% well retirement policy. Conversely, for farmers with at least one retired well, those with initially higher profitability, characterized by greater initial irrigation capacities and higher soil AWC, are subject to more declines in profit. For these farmers, the initial density of wells in their area does not appear to significantly influence changes in profit. In the case of authorized pump rate reduction policies, farmers in more well-populated areas and those with soils of higher AWC tend to be less negatively impacted by these policies. In contrast, a higher initial irrigation capacity is associated with greater declines in profit under the 50% authorized pump rate reduction policy.

Analysis of the data in Table 1 reveals that the directional trends and significance levels of coefficients for every policy scenario are consistent under both RCPs. However, the magnitude of these coefficients is generally lower under RCP8.5, suggesting a reduced influence of policies on profit. This reduction in influence is likely due to the substantial increase in temperatures under RCP8.5, which overtakes groundwater availability as the primary constraint on irrigated corn production.

Table 5.1. Estimated intercept and slope coefficients from the ordinary least squares (OLS) model, which quantifies the change in net present value (NPV) of profit from 2019 to 2099 per unit land area for individual farmers under each policy scenario, relative to the no-action scenario.

Policy	No. of Observations	RCP 4.5				RCP 8.5			
		Intercept	Initial irrigation capacity	Initial well density	Soil AWC	Intercept	Initial irrigation capacity	Initial well density	Soil AWC
10% Land Retirement	2827	313.0*** (79.57)	-1.34*** (0.33)	5.33* (2.87)	-2,303.5*** (431.0)	213.2*** (68.92)	-0.92*** (0.29)	4.41* (2.49)	-1,805.4*** (373.3)
30% Land Retirement	2827	1,025.3*** (192.1)	-25.35*** (0.80)	34.43*** (6.93)	-7,516.0*** (1,040.8)	662.5*** (166.9)	-21.65*** (0.69)	28.10*** (6.02)	-5,639.9*** (904.0)
50% Land Retirement	2827	74.1 (265.6)	-57.77*** (1.10)	46.98*** (9.58)	-6,484.2*** (1,438.7)	-349.7 (229.6)	-49.65*** (0.95)	36.82*** (8.29)	-4,039.4*** (1,243.9)
10% Well Retirement (non-enrolled)	2489	121.2*** (26.89)	-0.80*** (0.11)	13.13*** (0.98)	682.8*** (146.3)	110.5*** (22.67)	-0.76*** (0.10)	10.84*** (0.82)	541.1*** (123.4)
30% Well Retirement (non-enrolled)	1857	593.5*** (67.44)	-3.04*** (0.30)	38.85*** (2.45)	1,187.4*** (366.6)	495.0*** (57.26)	-2.80*** (0.25)	31.76*** (2.08)	988.2*** (311.2)
50% Well Retirement (non-enrolled)	1295	989.3*** (119.8)	-5.91*** (0.52)	79.68*** (4.48)	905.2 (653.1)	794.1*** (102.1)	-5.29*** (0.44)	64.22*** (3.82)	895.9 (556.3)
10% Well Retirement (enrolled)	338	-9,237.2*** (1,786.2)	-2.54 (6.61)	104.63* (60.7)	-30,030*** (9,287.2)	-8,462.6*** (1,563.3)	-1.54 (5.79)	86.14 (53.1)	-24,600*** (8,128.6)
30% Well Retirement (enrolled)	970	-9,433.4*** (952.1)	-22.61*** (3.54)	26.95 (33.8)	-10,080** (5,111.2)	-8,643.7*** (831.5)	-19.11*** (3.09)	16.88 (29.51)	-7,164.4 (4,464.0)
50% Well Retirement (enrolled)	1532	-8,294.3*** (702.6)	-37.82*** (2.81)	15.33 (24.4)	-8,810.2** (3,782.9)	-7,696.6*** (612.3)	-32.23*** (2.45)	8.42 (21.27)	-5,897.8* (3,296.9)
10% Pump Rate Reduction	2827	-198.3*** (24.14)	0.16 (0.10)	5.97*** (0.87)	745.7*** (130.8)	-152.9*** (20.23)	0.07 (0.08)	5.02*** (0.73)	567.9*** (109.6)
30% Pump Rate Reduction	2827	-1,004.7*** (89.78)	0.53 (0.37)	34.59*** (3.24)	3,397.8*** (486.4)	-779.6*** (75.73)	0.23 (0.31)	29.49*** (2.73)	2,462.3*** (410.3)
50% Pump Rate Reduction	2827	-2,712.5*** (195.2)	-1.38* (0.81)	86.2*** (7.04)	7,458.0*** (1,057.6)	-2,143.9*** (163.7)	-1.39** (0.68)	72.52*** (5.91)	5,280.1*** (886.9)

Note: Initial irrigation capacity is defined as the ratio of the combined capacity of a farmer's irrigation wells to their total farm area in 2018, expressed in CMD/ha, where CMD stands for cubic meters per day. Initial well density is the number of active irrigation wells within a 3000-m radius of each farm's centroid in 2018. AWC represents the available water capacity of the dominant soil type within each farm, which is calculated as a weighted average over a 1m depth and expressed as a ratio (cm/cm). Significance levels are indicated by * ($p < 0.1$), ** ($p < 0.05$), and *** ($p < 0.01$). Coefficient estimates are accompanied by their standard errors in parentheses. For well retirement policies, two categories of outputs are provided: "non-enrolled", referring to farmers who have not retired any wells, and "enrolled", for farmers who have retired at least one well.

5.3.3. Hydrologic Outcomes

While total groundwater storage in the study area consistently decreases over time for both RCPs under the no-action scenario (Figure 5.9 and Figure C37 in the Appendix C), the rate of depletion reduces over time. This slowdown stems from diminished well capacity and increasingly

adverse climate conditions for growing irrigated corn, which is a water-intensive crop, leading to declining irrigation demand and groundwater extraction over time without any policy interventions. The downward trend in groundwater storage moderates with the implementation of groundwater management policies, especially when 50% of the irrigated lands or wells are retired. The variability in groundwater storage projections increases over time, reflecting the cumulative uncertainties that arise from incorporating different GCMs in the ABM-MODFLOW simulations. Under RCP8.5, projections show a slight increase in groundwater storage levels by the end of the century across all management scenarios, compared to RCP4.5. This increase is attributed to the majority of farmers transitioning from irrigated corn to winter wheat by mid-century under all climate projections for RCP8.5. The average capacity of active irrigation wells, those that are neither retired nor dried out, follows a trend similar to groundwater storage (Figures C38 and C39 in the Appendix C).

As indicated earlier, region-wide groundwater extraction for irrigation demonstrates a decreasing trend over time under the no-action scenario for both RCPs (Figures C40 and C41 in the Appendix C). However, with policy implementation, this trend becomes less steep due to the initial reduction in groundwater use, which contributes to sustained well capacities. Over time, the difference in downward trends results in the convergence of groundwater extractions under the no-action scenario with those under policy interventions.

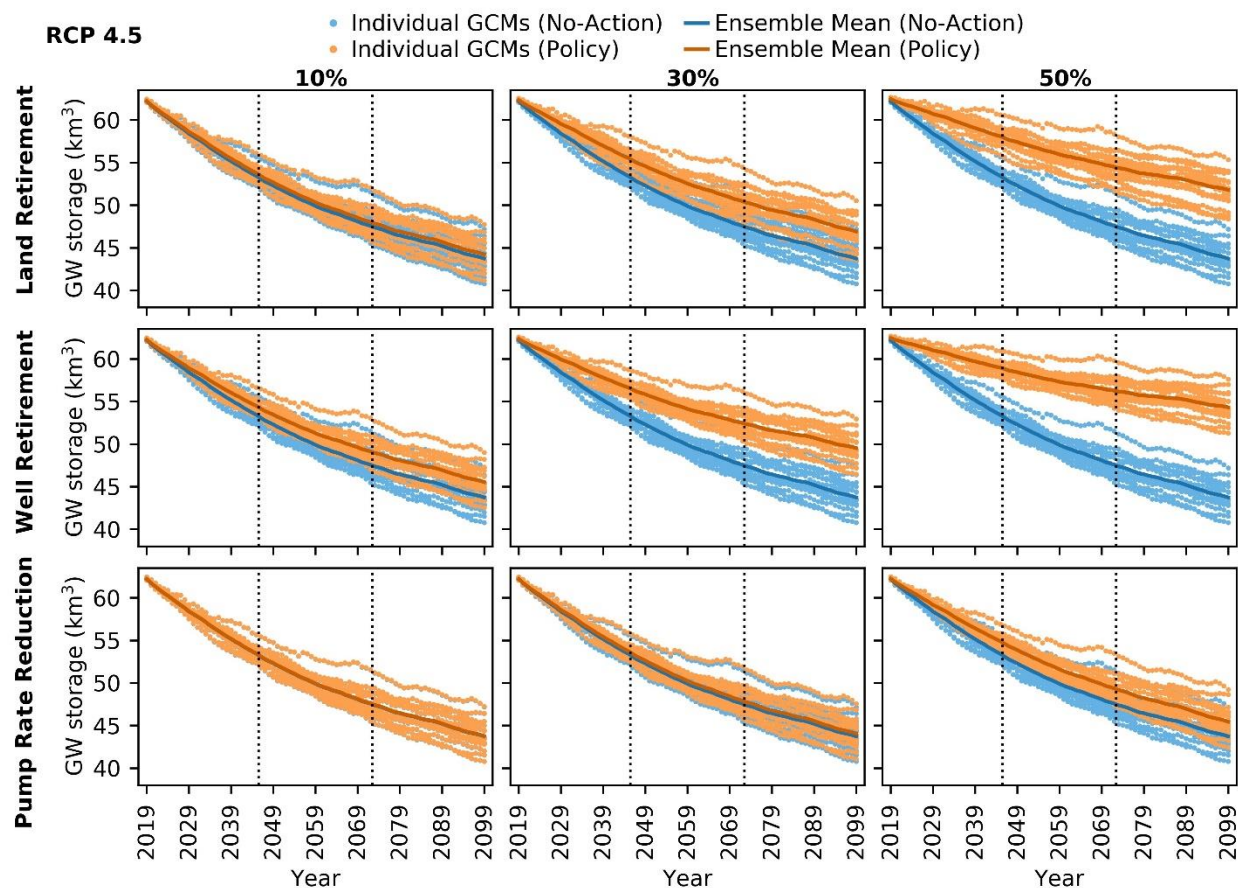


Figure 5.9. Total groundwater storage in the study area as simulated by the ABM-MODFLOW, based on an ensemble of global climate models (GCMs) projections for RCP4.5 under various management scenarios. Dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).

Projections of total groundwater recharge in the study area show no significant temporal trend under all management scenarios for both RCPs (Figures C42 and C43 in the Appendix C). For RCP4.5, the overall stability in recharge stems from the lack of a significant trend in precipitation projections, which predominates in the recharge process. Although irrigation return recharge decreases over time due to reduced groundwater extraction for irrigation, this reduction does not significantly alter the overall trend in total recharge. Under RCP8.5, while projections indicate an upward trend in winter and spring precipitation, this is counterbalanced by a larger decrease in irrigation return recharge compared to RCP4.5, resulting in no net change in total

recharge. Land retirement and well retirement policies, when implemented at high levels, lead to a slight decrease in total recharge via two mechanisms: firstly, by reducing enhanced precipitation recharge due to a decreased irrigated area; and secondly, by diminishing irrigation return recharge as result of reduced irrigation. The ABM-MODFLOW simulates recharge as an instantaneous process rather than a delayed one, which is estimated to take decades to affect the groundwater system in the region (McMahon et al., 2006). Nevertheless, the model still accounts for the impact of reduced recharge on the effectiveness of groundwater management policies in extending the aquifer's lifespan, although not in terms of a lagged hydrologic response (Glose et al., 2022).

Figure 5.10 demonstrates the effects of groundwater management policies on the aquifer's saturated thickness across the region. It contrasts the projected saturated thickness in 2099 under the no-action scenario for RCP4.5 (Figure 5.10a) with the relative change in saturated thickness in 2099 resulting from policy interventions (Figure 5.10b). This comparison highlights that the policies have a more substantial impact on areas with thicker portions of the aquifer, where groundwater extraction is more intense; e.g., areas in Yuma, Cheyenne, and Sherman counties. This pattern is consistent in the projections for RCP8.5 (Figure C44 in the Appendix C).

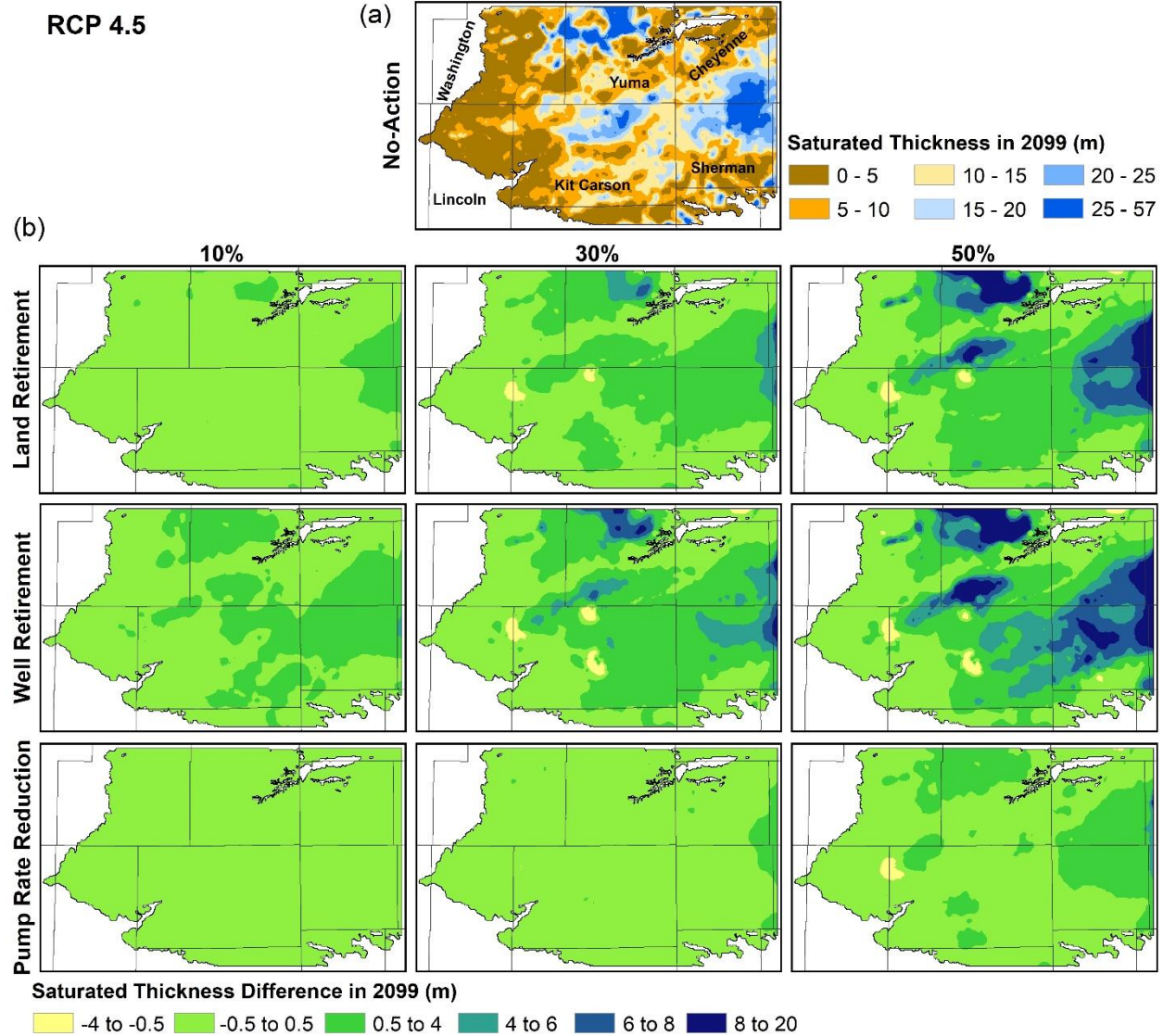


Figure 5.10. Influence of groundwater management policies on the aquifer's saturated thickness across the region under RCP4.5. (a) Saturated thickness in 2099 under the no-action scenario, calculated as the ensemble mean of simulation outcomes under climate projections from multiple global climate models (GCMs). (b) Change in saturated thickness in 2099, relative to the no-action scenario, under different groundwater management policies.

To assess the impacts of groundwater management policies on stream baseflows, we select five observation points and compare the average simulated baseflows for October, representing the post-irrigation low-flow period, across different management scenarios. These points are positioned at the outlets of major streams within the ABM-MODFLOW domain (Figure 5.1b). For

the South Fork Republican River, rather than considering the outlet, we choose a stream gauge near the Colorado-Kansas border as our observation point. This is because the South Fork Republican River becomes a losing stream downstream of the stream gauge, and a portion of baseflow returns to the aquifer. The outlet of Beaver Creek, which consistently showed zero baseflows across all simulations, is omitted from our analysis. Results indicate that implementing land and well retirement policies at 30% and 50% levels leads to sizable increases in baseflows, relative to the no-action scenario, whereas the authorized pump rate reduction policy instrument is less effective (Figures C45 to C52). The impact of policies, however, varies across different streams. Notably, baseflow in the North Fork Republican River stabilizes or even increases over time from the beginning of implementing the 50% land and well retirement policies. This immediate stabilization is likely due to considerably reduced water withdrawals from the cluster of high-capacity wells near the stream in Yuma County, coupled with significant recharge through the area's sandy soils. Under RCP8.5, baseflows are marginally higher across the streams compared to those under RCP4.5, under all management scenarios. This difference is attributed to reduced groundwater extraction for irrigation, as a result of a more rapid and widespread shift from water-intensive irrigated corn to less water-demanding winter wheat under RCP8.5.

5.3.4. Comparison of Policy Outcomes

Figure 5.11 presents the region-wide effects of different groundwater management policies on farmers' profitability and the natural system under RCP4.5. The impact on profitability is represented by the percent decrease in *NPV* of region-wide profits from 2019 to 2099, relative to the no-action scenario. The effects on the natural system are quantified by two metrics: the percent increase in the total volume of October baseflows at selected observation points (Figure 5.1b) between 2019 and 2099, and the percent increase in groundwater storage in 2099, both compared

to the no-action scenario. Among the policy instruments considered for this study, well retirement has the most significant impacts on both economic and environmental aspects, followed by land retirement. In contrast, the authorized pump rate reduction policy instrument exhibits the least impact, which stems from the fact that the current well capacity is considerably below the authorized pump rate for most wells in the region; therefore, even a 30% reduction in authorized pump rates fails to produce significant changes. When compared to other policy instruments, the authorized pump rate reduction policies result in smaller increases in baseflow and groundwater storage for a greater decrease in *NPV*. This is because farmers, constrained by lower maximum pump rates, continue to irrigate but switch to winter wheat, which has a significantly lower irrigation value than corn. These findings are similar for RCP8.5 (Figure C53 in the Appendix C).

The actual values corresponding to the percent differences are listed in Table C6 of the Appendix C. Additionally, we conduct a sensitivity analysis to assess the impact of the discount rate on policy outcomes. We compute *NPV* of region-wide profit using discount rates of 3% and 7% and compare these to the outcomes obtained with a 5% discount rate, as detailed in Table C7 of the Appendix C. Although a lower discount rate reduces the losses from policy interventions across all cases, the relative differences among the policies remain consistent.

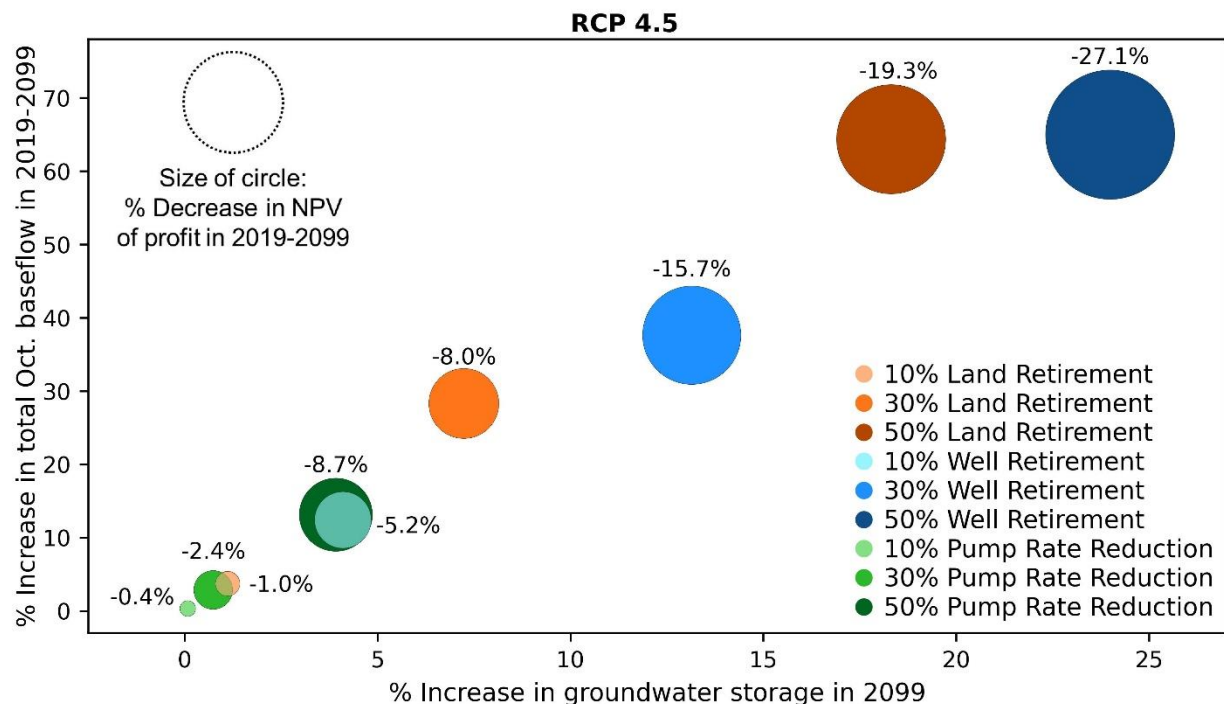


Figure 5.11. Comparison of region-wide policy outcomes under RCP4.5. All percent change values are calculated relative to the no-action scenario, based on the ensemble mean of simulation outputs from multiple global climate models (GCMs). *NPV* stands for net present value.

5.4. Discussion and Conclusion

The simulation outcomes from the ABM-MODFLOW offer valuable insights into the coevolution of human activities, crops, and groundwater system in semi-arid agricultural regions amidst climate change, both in scenarios with and without policy interventions. Initially considering the scenarios without any groundwater management policies, we observe the rate of groundwater depletion slows over time, contrary to the prevailing assumption that climate change, characterized by elevated temperatures and more severe droughts, would exacerbate groundwater depletion due to increased irrigation demands (Famiglietti, 2014; Scanlon et al., 2012; Taylor et al., 2013). This counterintuitive slowdown in depletion rate is driven by reductions in well capacity and the effect of rising summer temperatures, both of which hinder irrigated corn production, prompting a shift

towards irrigated winter wheat cultivation. Farmers with lower profitability margins, marked by lower initial irrigation capacities and lower soil *AWC* values, find themselves less equipped to buffer against adverse climate conditions affecting corn production, thus transitioning sooner to winter wheat.

Winter wheat emerges as a resilient alternative, since it is a less water-intensive crop, skips peak summer temperatures, and benefits from warmer springs reducing frost risks. Furthermore, winter wheat capitalizes on increased CO₂ levels, which boosts its photosynthesis, growth, and yield, whereas corn has a limited capacity to benefit from elevated CO₂ levels (Ahmed et al., 2019; Deryng et al., 2016; Kimball, 2016; Tausz et al., 2013). Economic factors hence play a crucial role in dictating groundwater depletion trajectories. Over time, irrigated corn becomes less profitable while winter wheat gains financial attractiveness, leading to a shift in crop preferences that ultimately reduces irrigation demands and groundwater extraction. Notably, under the more severe greenhouse gas emission scenario, RCP8.5, groundwater storage levels by the end of the century are slightly higher than those under RCP4.5. This increase is attributed to the combined effect of higher temperatures and elevated CO₂ levels that disadvantage corn relative to winter wheat, accelerating the crop transition under RCP8.5. However, farmers with larger initial irrigation capacities experience a drop in *NPV* of their profits under RCP8.5 compared to RCP4.5, owing to the immediate negative impacts of rising temperatures on irrigated corn.

These complex system dynamics underscore the significance of indirect effects of climate change on groundwater systems, challenging the reliability of long-term groundwater projections from models that fail to incorporate the complex interplay between human activities, crops, and groundwater system in the context of climate change. Current literature, whether employing standalone groundwater models (Chen et al., 2023; Ou et al., 2018; Peterson et al., 2020), coupled

agronomic-groundwater models (Kumar et al., 2023), or hydro-economic models (Hrozencik et al., 2017; Khan and Brown, 2019), generally does not account for such complex interactions.

Region-wide undiscounted annual profit trajectories differ under the two RCP scenarios. Under RCP4.5, there is an L-shaped trend, indicating a stabilization of profits after an initial declining trend, while RCP8.5 exhibits a U-shaped trend, where profits eventually enter a rising trend after the initial decreasing trend and following stagnation. The initial downward trend in both cases can be ascribed to the dual pressure of increasing temperatures and diminishing well capacity affecting irrigated corn production. For RCP4.5, a stabilization in profits occurs as temperatures rise to levels limiting corn growth, thereby making irrigated winter wheat the dominant crop. The rising trend in winter wheat yields mitigates the impacts of reduced well capacity on its production. Under RCP8.5, the increasing yields of winter wheat gradually outweigh the impact of well capacity, contributing to an upward trend in annual profits in the long-term.

The introduction of groundwater management policies into simulations causes an initial drop in region-wide undiscounted annual profits, reflecting the initial cost of reduced water use. Over time, however, these profits begin to converge with those projected under the no-action scenario for both RCPs, across all policy instruments. This convergence occurs as farmers adjust their crop choices from corn to winter wheat in response to rising temperatures, along with sustained well capacity due to these policies, which enhances yields for both irrigated corn and winter wheat in the long-term. However, profits under policy interventions never surpass the baseline profits. This is because the early conserved groundwater is predominantly used for winter wheat irrigation in the later years, which has a substantially lower value for irrigation than corn (Smidt et al., 2016). Hence, while groundwater management policies have a sizable positive impact on groundwater storage and stream baseflows, their economic benefits are hampered by climate change as irrigated

corn production becomes constrained in the future. From the perspective of weak sustainability, which assumes natural (groundwater) and human capital (increased profits) are substitutes (Neumayer, 2013), one might advocate for unrestricted groundwater use in the short-term to maximize profits from irrigated corn production while climatic conditions permit. Conversely, proponents of strong sustainability, viewing natural capital as irreplaceable (Neumayer, 2013; Pearce and Atkinson, 1993), would argue for the conservation of groundwater for future generations.

Exploring the percent change in *NPV* of individual farmers' profits, compared to the baseline, under different groundwater management policies reveals the heterogeneous impacts of each policy across farmers. Firstly, land retirement policies lead to greater losses for farmers with higher profitability, since they are required to halt irrigation on parts of their farm despite having soil with high water-holding capacity and abundant irrigation capacity. In areas with higher well density, farmers tend to benefit more from these policies. Secondly, well retirement policies result in a high variability in *NPV* changes among farmers; those without retired wells see considerable gains, while farmers with at least one retired well and with initially higher profitability face significant losses. Notably, farmers with lower initial irrigation capacities and no retired wells generally benefit more from the retirement of their nearby wells, a finding corroborated by Manning et al. (2020). Within the cohort of farmers with no retired wells, those in areas with more wells and those with soils of higher *AWC* typically benefit more from well retirement policies.

Thirdly, under authorized pump rate reduction policies, farmers in areas with a higher well density and those with soils of greater *AWC* tend to experience less negative impact from these policies. The mitigating effect of greater *AWC* suggests that when maximum pump rates are restricted, farmers with soils that have a higher water-holding capacity can more effectively utilize stored

precipitation water in the soil profile. Lastly, observing that all three policy instruments have more favorable outcomes in regions with a high density of wells accentuates the adverse effect of pumping externalities on farmers' profitability.

The outputs of the ABM-MODFLOW are subject to a range of uncertainties, as is typical with any long-term projection of coupled human-natural systems. Firstly, we assume constant crop prices throughout the simulation period, a simplification that overlooks potential variations in prices due to both regional and global factors, such as global declines in corn productivity and rises in wheat productivity, as projected by Jägermeyr et al. (2021). Secondly, our model does not account for adaptive measures by farmers, such as shifting planting dates or changing cultivars, potentially overestimating the agricultural costs of climate change (Mendelsohn et al., 1994; Minoli et al., 2022; Rouhi Rad et al., 2020b). Furthermore, our focus on corn and winter wheat, as the primary crops in the region, does not capture potential future shifts to other crops, particularly forage crops given the growing meat and dairy industry in the region.

Lastly, crop growth simulations are subject to significant uncertainties, particularly due to the effects of rising CO₂ levels, which are recognized as one of the principal sources of uncertainty in long-term crop yield projections (Ahmed et al., 2019; Jägermeyr et al., 2021). To account for these uncertainties, it is recommended to use an ensemble of crop models (Ahmed et al., 2019). However, this approach is not foolproof, as it cannot fully capture the intricacies of crop responses to climate variability; simulations in most crop models are carried out on a daily time step, which fails to account for sub-daily climatic stressors. Stressors like compound hot-dry-windy events, which can occur on an hourly basis, are known to severely affect wheat yields in the U.S. Great Plains (Zhao et al., 2022).

Future research should consider quantifying the uncertainties inherent in the ABM-MODFLOW simulation outcomes. Additionally, exploring incentive-based policy instruments, such as groundwater markets, could provide valuable insights beyond those offered by traditional centralized governance approaches (Khan and Brown, 2019). Lastly, given that uniform policies result in heterogeneous outcomes for both farmers and the natural system across space and time, future studies might evaluate the impact of policies that are spatially variable and adjusted dynamically over time.

CHAPTER 6.

SUMMARY AND FUTURE RESEARCH DIRECTION

6.1. Summary and Closing Remarks

Semi-arid agricultural regions worldwide are heavily dependent on groundwater storage in a handful of large and over-exploited aquifers, such as the High Plains Aquifer (HPA) in the U.S. High Plains Region. The HPA stands as one of the world's largest freshwater aquifers and serves as the primary source of irrigation water in the High Plains Region. The socioeconomic development in the High Plains Region has been achieved at the cost of substantial groundwater depletion in the HPA, which shows the highest average depletion rate among major aquifer systems in the U.S. The ongoing depletion of the HPA not only endangers the livelihoods of rural communities reliant on irrigated agriculture for income and employment, but also poses a threat to national food security. Furthermore, climate projections suggest the High Plains Region will face substantially drier conditions in the latter half of the 21st century, which could amplify irrigation demands and expedite groundwater depletion.

Dealing with this challenge necessitates the implementation of effective groundwater management policies that aim to extend the lifespan of the HPA while also minimizing costs for farmers. This dissertation aims to enhance the capacity to project the future of groundwater systems in semi-arid agricultural regions, particularly the High Plains Region, as a coupled human-natural system, considering the impacts of climate change and various policy scenarios. To achieve this goal, a number of tools were developed that incorporate a spectrum of modeling techniques, from the increasingly popular data-driven models to the cutting-edge hydro-economic models.

Firstly, a data-driven modeling framework was developed that utilizes the random forests (RF) technique in combination with ordinary kriging to spatiotemporally project future groundwater levels (GWLs) as a function of climatic and anthropogenic factors. The developed modeling framework was tested for the HPA in Finney County, located in southwest Kansas. This region is known for intensive groundwater irrigation and has experienced notable groundwater depletion in recent years. In this modeling framework, instead of developing individual models for each monitoring well, a single RF model was trained, calibrated, and tested using all historical GWL measurements across the study area.

Among the various input variables considered in the RF model, the Introduction of groundwater withdrawal potential (*GWWP*), defined as the product of saturated thickness and the number of active high-production wells, provides the RF model with the capability to capture the decline in groundwater depletion rate as the system advances towards aquifer depletion. Additionally, *GWWP* equips the RF model with the ability to assess the effects of well retirement policies on future GWLs. The sensitivity analysis highlights the significant influence of *GWWP* compared to the other input variables. The assessment of the RF model's generalization abilities from various angles indicates its satisfactory performance, considering its simplicity with respect to development and calibration.

Simulations projecting into the 21st century, accounting for climate impacts, present a grim outlook for future groundwater availability in the study area under status quo conditions. The findings indicate that, assuming the worst, average, and best climate conditions, respectively, the majority of the aquifer's extent will no longer be able to sustain irrigated agriculture by 2050, 2060, and 2070. The results also suggest that while climate plays a significant role in groundwater depletion trends in areas with limited saturated thickness and low well density, it is likely to alter

the timeframe for aquifer depletion by 15 years or less in the majority of the study area. Furthermore, it appears that greenhouse gas emissions do not exert a significant influence on groundwater availability in the county.

Simulations, incorporating the combined effects of management and climate conditions, suggest that while well retirement plans result in initial groundwater savings in the county, these savings are not sustained over the long term due to increased groundwater withdrawals from the remaining wells. Additionally, the results indicate that the effectiveness of the retirement plans is impeded by the drier climate conditions anticipated in the latter half of the century, attributed to greenhouse gas emissions.

Overall, the developed data-driven modeling framework holds promise in capturing long-term climatological and regulatory impacts on groundwater availability in intensively irrigated regions. The modeling framework can function as a rapid assessment tool, providing policymakers with valuable insights into future groundwater availability at the county level, under varying climate and management scenarios. This tool aids policymakers in gauging the urgency of implementing adaptation and conservation strategies to address groundwater depletion across the High Plains Region.

Secondly, a spatiotemporally explicit agent-based hydro-economic model (ABM-MODFLOW) was developed for an intensively groundwater-fed irrigated region in eastern Colorado and northwest Kansas within the High Plains Region. The ABM-MODFLOW encompasses three key components: a spatially distributed groundwater model (MODFLOW) that provides complete control over groundwater diversion and recharge at every irrigation well and pertinent irrigated parcel, an agronomic model (DSSAT) that simulates the biophysical processes governing crop growth and development, and an economic model that explicitly simulates

irrigation and planting decisions of individual agents (farmers) within a stochastic framework, based on the outputs of the agronomic model. The developed model was designed to capture dynamic feedbacks within a coupled human-groundwater system in irrigated regions and each modeling component was developed through interdisciplinary collaboration to meet specific research objectives. A unique feature of the model is the attention to detail in the creation of agents, ensuring they closely represent real-world farmers. Moreover, well capacity, a factor often neglected in existing literature, was integrated as a constraint on the duration of irrigation applications.

The thorough validation of the ABM-MODFLOW against historical data highlights its satisfactory performance in simulating various aspects of the coupled human-natural system. This underscores its reliability in assessing different policy instruments. Furthermore, when compared against the standalone MODFLOW model, integrating the groundwater model with economic and agronomic models does not compromise hydrologic outputs but rather enhances the precision of simulated groundwater levels. This improved precision chiefly stems from a more accurate calculation of withdrawals from irrigation wells.

The analysis of system dynamics offers valuable policy insights. Among agents with low irrigation capacity, there is high variability in annual profits, suggesting a need for spatially heterogeneous policy designs for this group. Conversely, given the considerable administrative and enforcement costs associated with heterogeneous policies and lower variability in annual profits among agents with medium or high irrigation capacities, implementing uniform conservation policies for these agents might be more efficient. Moreover, water conservation policies could pose higher costs for agents with coarser soils, due to these soils' limited capacity

to store precipitation water. Therefore, when formulating policies, it is crucial to account for soil type heterogeneity among agents.

Lastly, the ABM-MODFLOW was employed to project the coevolution of human activities, crops, and groundwater in semi-arid agricultural regions amidst climate change, both with and without policy interventions. The ABM-MODFLOW simulations involved 32 climate scenarios from 16 downscaled global climate models (GCMs) for two representative concentration pathways (RCPs), RCP4.5 and RCP8.5. Additionally, three groundwater management policy instruments were explored: irrigated land retirement, irrigation well retirement, and authorized pump rate reduction. In scenarios without any groundwater management policies, the findings indicate a deceleration in the rate of groundwater depletion over time, contrary to the prevailing assumption that climate change, characterized by elevated temperatures and more severe droughts, would exacerbate groundwater depletion due to increased irrigation demands. This counterintuitive slowdown in depletion rate is driven by reductions in well capacity and the effect of rising summer temperatures, both of which hinder irrigated corn production, prompting a shift towards irrigated winter wheat cultivation. Farmers with lower profitability margins, marked by lower initial irrigation capacities and lower soil available water capacity (AWC) values, find themselves less equipped to buffer against adverse climate conditions affecting corn production, thus transitioning sooner to winter wheat.

Winter wheat emerges as a resilient alternative, since it is a less water-intensive crop, skips peak summer temperatures, and benefits from warmer springs reducing frost risks. Furthermore, winter wheat capitalizes on increased atmospheric carbon dioxide concentration (CO₂) levels, which boosts its photosynthesis, growth, and yield, whereas corn has a limited capacity to benefit from elevated CO₂ levels. Economic factors hence play a crucial role in dictating groundwater

depletion trajectories. Over time, irrigated corn becomes less profitable while winter wheat gains financial attractiveness, leading to a shift in crop preferences that ultimately reduces irrigation demands and groundwater extraction. These complex system dynamics highlight the importance of considering the indirect effects of climate change on groundwater systems. They also emphasize the need for models to incorporate the complex interactions between human activities, crops, and the groundwater system in the context of climate change to ensure reliable long-term groundwater projections.

The region-wide undiscounted annual profit trajectories display distinct patterns under the two RCP scenarios. Under RCP4.5, there is an L-shaped trend, signifying a stabilization of profits after an initial decline. Conversely, RCP8.5 demonstrates a U-shaped trend, with profits eventually entering an upward trajectory after an initial decrease and subsequent period of stagnation. The initial decline in both cases can be attributed to the combined impact of rising temperatures and decreasing well capacity, which adversely affect irrigated corn production. Under RCP4.5, profit stabilization occurs as temperatures reach levels that limit corn growth, consequently making irrigated winter wheat the dominant crop. The increasing yields of winter wheat help alleviate the effects of reduced well capacity on its production. Under RCP8.5, the progressively improving yields of winter wheat gradually outweigh the impact of diminished well capacity, leading to an upward trend in annual profits in the long-term.

The introduction of groundwater management policies into simulations initially leads to a decrease in region-wide undiscounted annual profits, reflecting the initial cost of reduced water use. However, over time, these profits start to converge with those projected under the no-action scenario for both RCPs, across all policy instruments. This convergence occurs as farmers adjust their crop choices from corn to winter wheat in response to rising temperatures, along with

sustained well capacity due to these policies, which enhances yields for both irrigated corn and winter wheat in the long-term. However, profits under policy interventions never surpass the baseline profits. This is because the early conserved groundwater is predominantly used for winter wheat irrigation in the later years, which has a substantially lower value for irrigation than corn. Hence, while groundwater management policies have a sizable positive impact on groundwater storage and stream baseflows, their economic benefits are hampered by climate change as irrigated corn production becomes constrained in the future.

Exploring the percent change in net present value (*NPV*) of individual farmers' profits, compared to the baseline, under different groundwater management policies reveals the heterogeneous impacts of each policy across farmers. Land retirement policies lead to greater losses for farmers with higher profitability, since they are required to halt irrigation on parts of their farm despite having soil with high water-holding capacity and abundant irrigation capacity. In areas with higher well density, farmers tend to benefit more from these policies. Additionally, well retirement policies result in a high variability in *NPV* changes among farmers; those without retired wells see considerable gains, while farmers with at least one retired well and with initially higher profitability face significant losses. Notably, farmers with lower initial irrigation capacities and no retired wells generally benefit more from the retirement of their nearby wells. Within the cohort of farmers with no retired wells, those in areas with more wells and those with soils of higher *AWC* typically benefit more from well retirement policies. Furthermore, under authorized pump rate reduction policies, farmers in areas with a higher well density and those with soils of greater *AWC* tend to experience less negative impact from these policies. The mitigating effect of greater *AWC* suggests that when maximum pump rates are restricted, farmers with soils that have a higher water-holding capacity can more effectively utilize stored precipitation water in the soil

profile. Lastly, observing that all three policy instruments have more favorable outcomes in regions with a high density of wells accentuates the adverse effect of pumping externalities on farmers' profitability.

In general, this dissertation enhances the capacity for informed groundwater management in the face of climate change through a better understanding of groundwater systems' future in semi-arid agricultural regions with and without policy interventions. The developed data-driven modeling framework and the agent-based hydro-economic model provide valuable insights and policy implications for improving groundwater management in semi-arid agricultural regions.

6.2. Future research directions

Throughout the study period, several directions for future research were identified:

1. Considering the substitution of the Random Forest (RF) method with more recent and rigorously tested Machine Learning (ML) methods like deep learning techniques could potentially enhance the performance of the data-driven modeling framework.
2. Employing an ensemble of ML techniques in the data-driven modeling framework, instead of a single method like RF, may improve the accuracy of groundwater level (GWL) forecasts.
3. Another potential approach to enhancing GWL projections through data-driven models would involve grouping GWL measurement points into spatially homogeneous clusters. Subsequently, rather than creating a single model for all measurement points, distinct models would be generated for each cluster. This approach has the potential to result in more precise forecasts.

4. Assessing interpolation errors and their subsequent effects on the RF model outputs, given that the proposed data-driven modeling framework did not account for uncertainties in gridded data like saturated thickness and S_y .
5. There is a potential to relax the ABM-MODFLOW model's assumption of agent risk-neutrality. This can be accomplished by shifting from an expected profit maximization approach to a certainty equivalent maximization, which equals the expected profit minus the risk premium. With this modification, the model can account for behavioral heterogeneity among agents by specifying different values for the coefficient of risk aversion within the risk premium.
6. Conducting a global sensitivity analysis of the ABM-MODFLOW model would elucidate the impact of various parameters and inputs along with their uncertainties on the model's outcomes.
7. Incorporating an ensemble of crop simulation models within the ABM-MODFLOW model, rather than a single model like DSSAT, enables us to account for uncertainties in crop yield responses to rising atmospheric carbon dioxide concentration (CO_2) levels.
8. Exploring incentive-based policy instruments, such as groundwater markets, could provide valuable insights beyond those offered by traditional centralized governance approaches.
9. Evaluating the impact of policies that are spatially variable and adjusted dynamically over time, given that uniform policies result in heterogeneous outcomes for both farmers and the natural system across space and time.

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APPENDIX A

SUPPORTING INFORMATION FOR CHAPTER 2. EMPLOYING MACHINE LEARNING TO QUANTIFY LONG-TERM CLIMATOLOGICAL AND REGULATORY IMPACTS ON GROUNDWATER AVAILABILITY IN INTENSIVELY IRRIGATED REGIONS

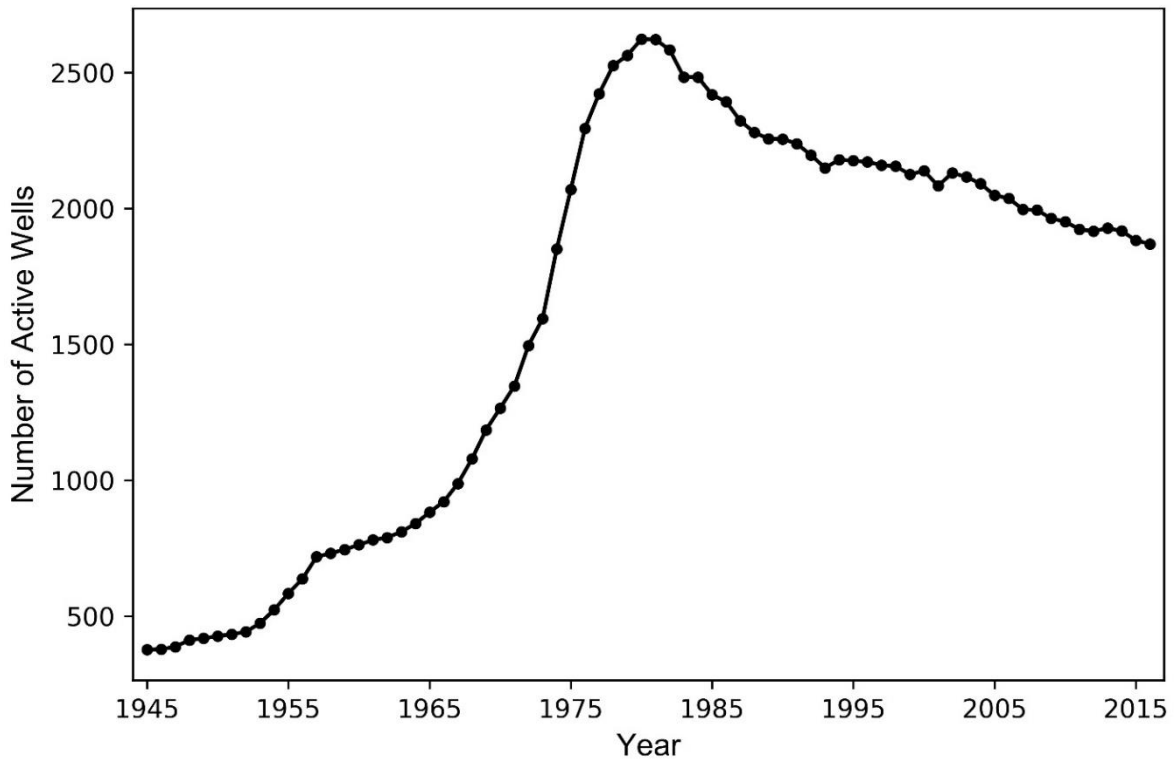


Figure A1. Number of active high production wells in Finney County during the 1945-2016 period. A given well is considered as high production if it is being used for irrigation, industrial, or municipal demands. Source of data is the Water Information Management and Analysis System (WIMAS; Kansas Geological Survey, 2019c).

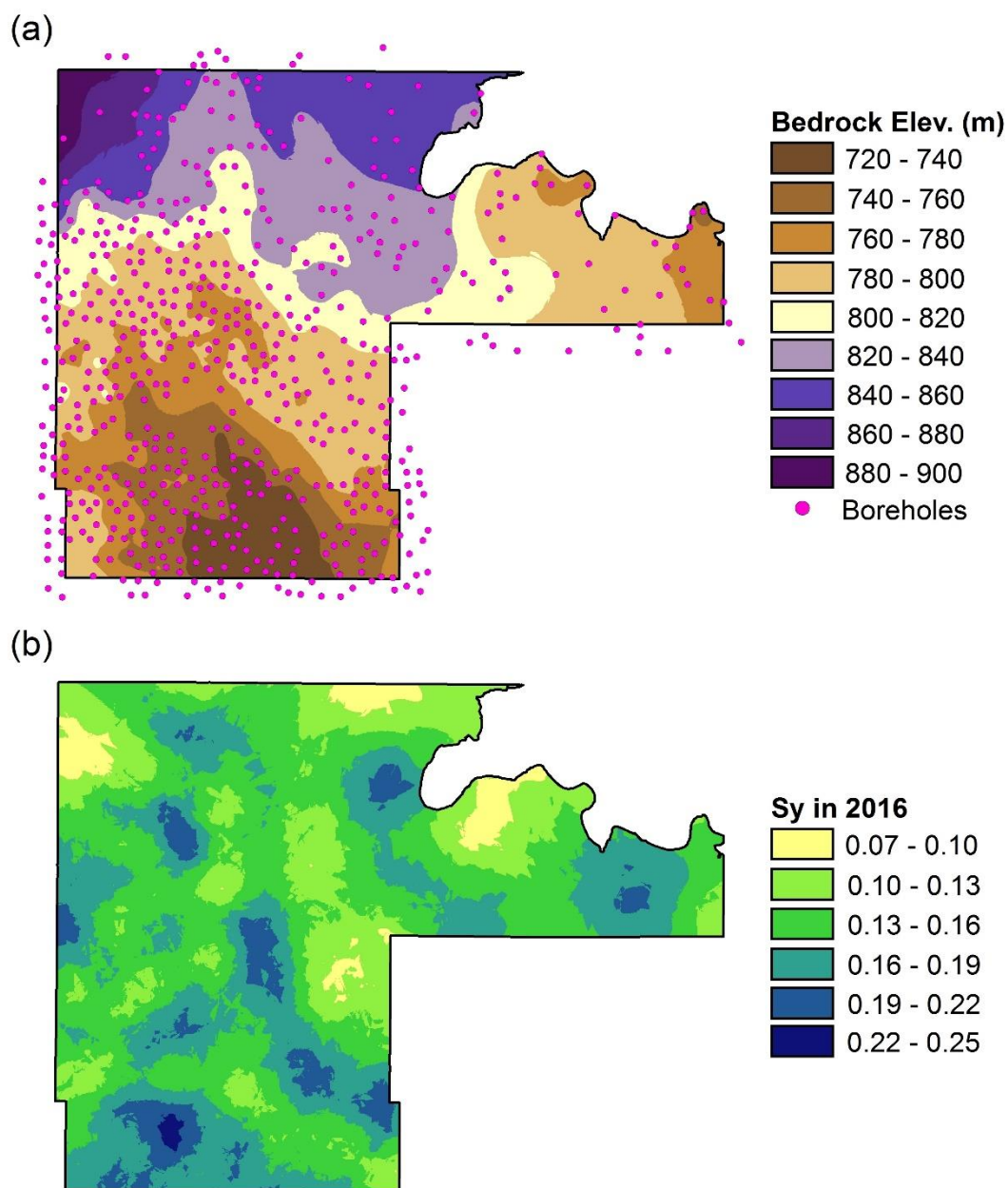


Figure A2. Geologic properties of the Ogallala Aquifer in Finney County. a) Boreholes in the county and its immediate vicinity and bedrock elevation. b) Map of aquifer specific yield (S_y) at groundwater level (GWL) in 2016. Map properties (bedrock elevation and S_y) were estimated using measurements from boreholes shown in *a*.

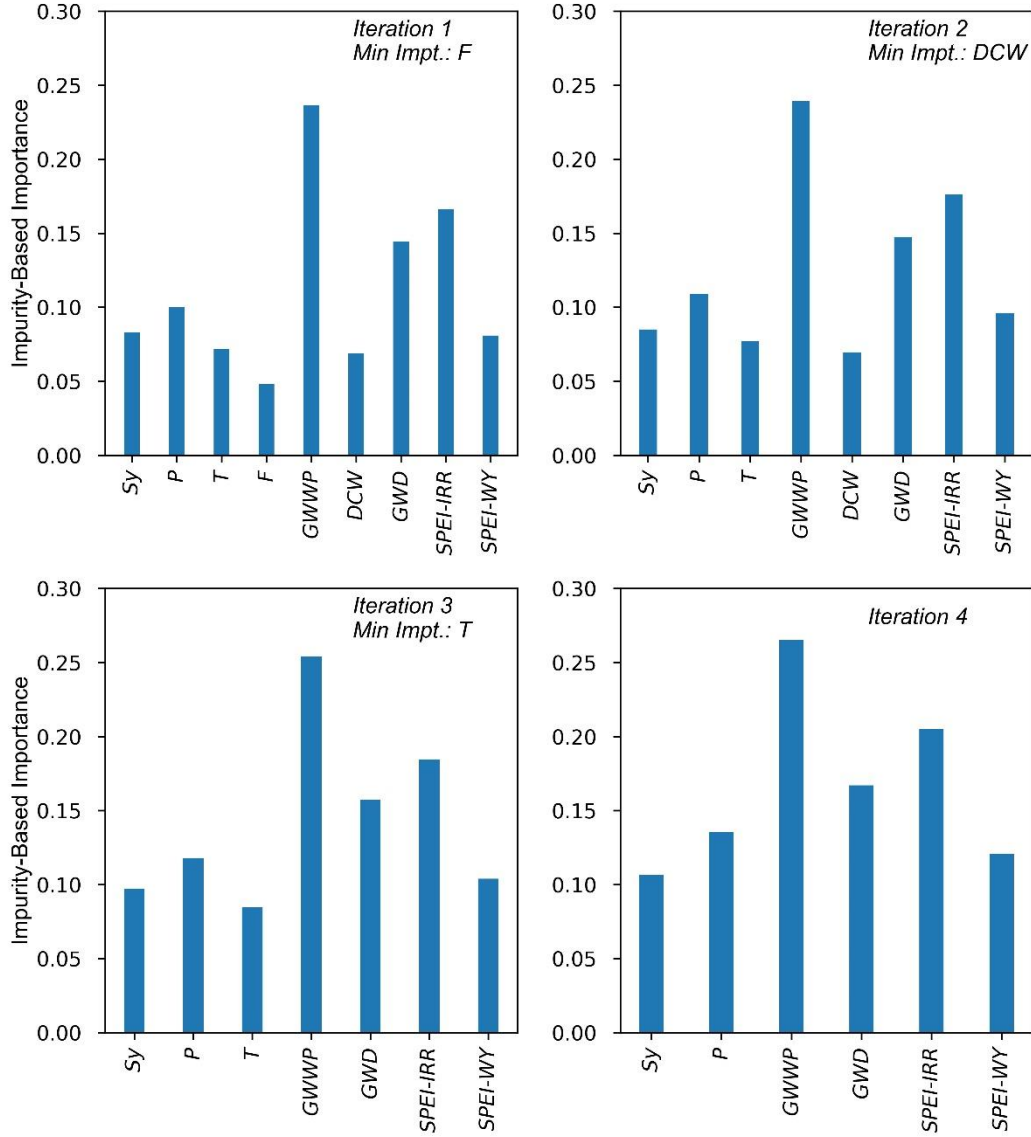


Figure A3. The recursive process employed for input variable selection in this study. The initial input variables considered for the random forests (RF) model are aquifer specific yield at groundwater level (*Sy*), water year total precipitation (*P*), average daily mean temperature in irrigation period (*T*), water year mean river flow (*F*), groundwater withdrawal potential (*GWWP*), distance to closest active well (*DCW*), groundwater depth (*GWD*), mean SPEI-3 in irrigation period (*SPEI-IRR*), and mean SPEI-3 in water year (*SPEI-WY*). SPEI-3 denotes the standardized precipitation evapotranspiration index (SPEI; Vicente-Serrano et al., 2010) with the aggregation time step of three months. The irrigation period is defined as May through September. Each plot represents an iteration through which the impurity-based importance of available input variables is computed using a random forests (RF) model and the feature with minimum importance (Min Impt.) is detected and omitted from the succeeding iteration. The RF model developed for each iteration consists of 500 trees and is trained with historical data from 1980 to 2011. At each split, the RF model explores all available input variables for the best split value, rather than search through a random subset of them. The recursive process is repeated until all remaining input variables attain an impurity-based importance value of greater than or equal to 0.1, which is achieved in the fourth iteration. The most relevant input variables determined through this procedure are *GWWP*, *SPEI-IRR*, *GWD*, *P*, *SPEI-WY*, and *Sy*.

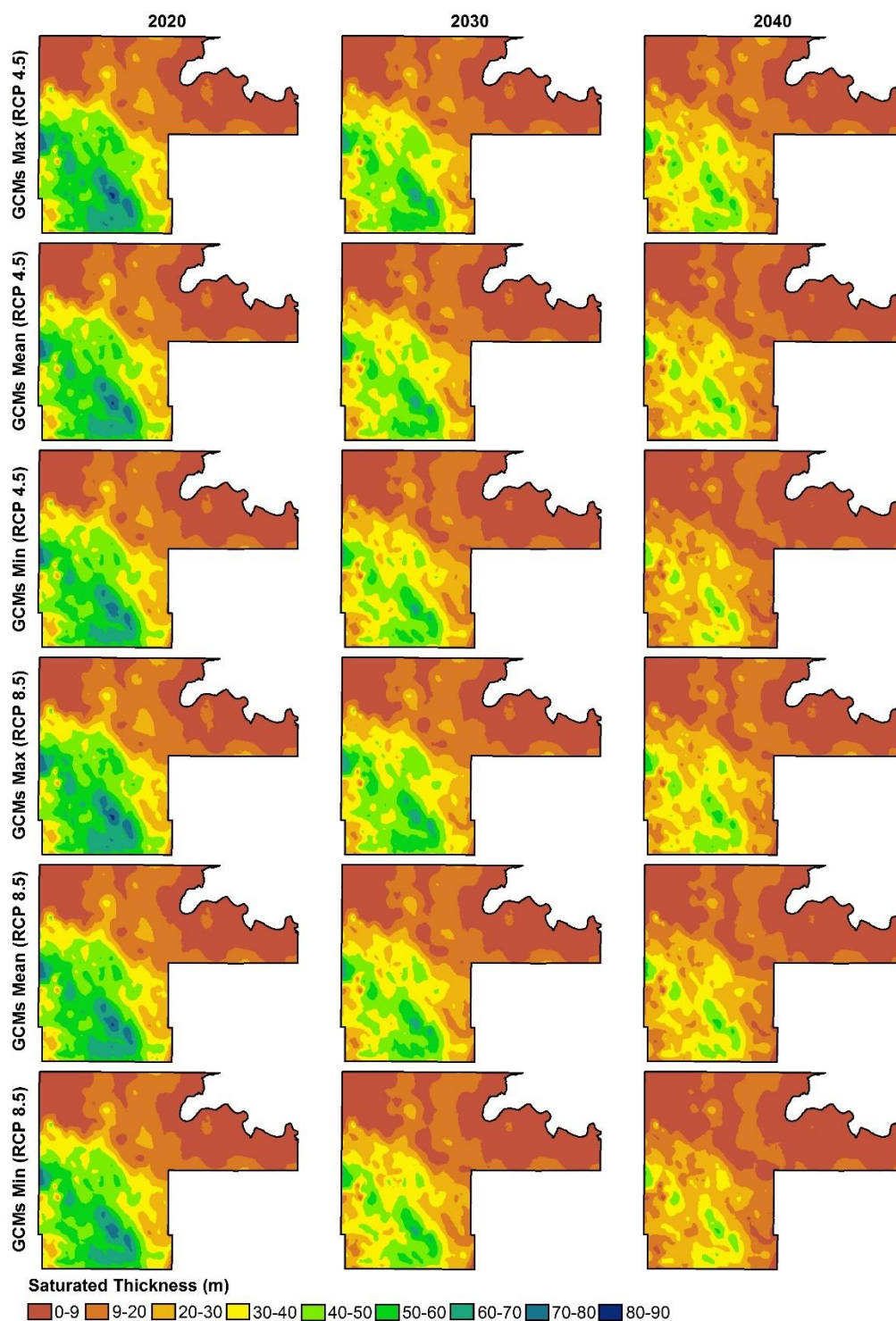


Figure A4. Gridded data of the minimum (GCMs Min), maximum (GCMs Max), and ensemble mean (GCMs Mean) of projected saturated thickness values in 2020, 2030, and 2040. Projected saturated thickness values are obtained through running the random forests (RF) model for various climate scenarios developed based on the downscaled climatic data of 20 global climate models (GCMs) for two different representative concentration pathways (RCP) scenarios, namely RCP 4.5 and RCP 8.5.

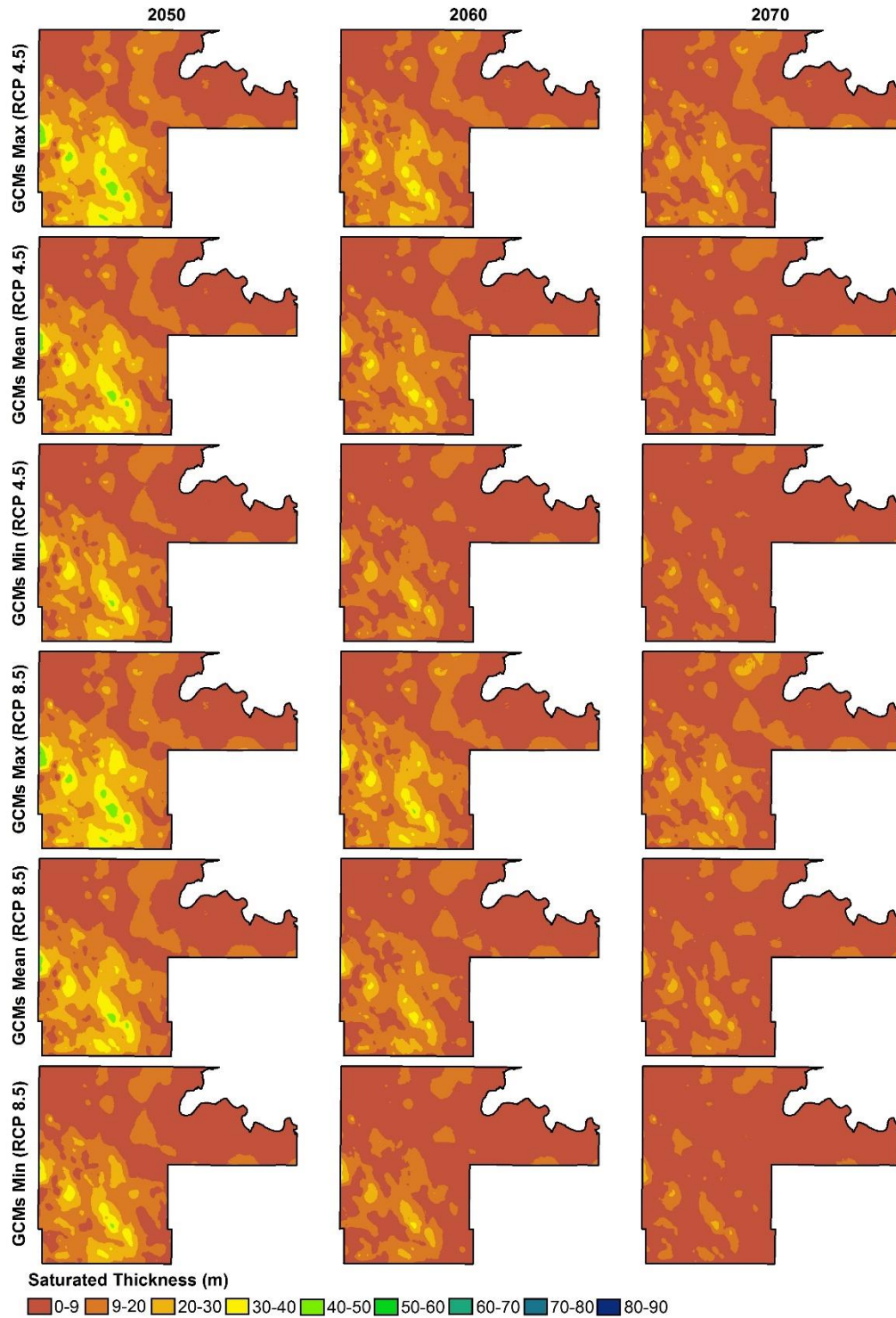


Figure A5. Gridded data of the minimum (GCMs Min), maximum (GCMs Max), and ensemble mean (GCMs Mean) of projected saturated thickness values in 2050, 2060, and 2070. Projected saturated thickness values are obtained through running the random forests (RF) model for various climate scenarios developed based on the downscaled climatic data of 20 global climate models (GCMs) for two different representative concentration pathways (RCP) scenarios, namely RCP 4.5 and RCP 8.5.

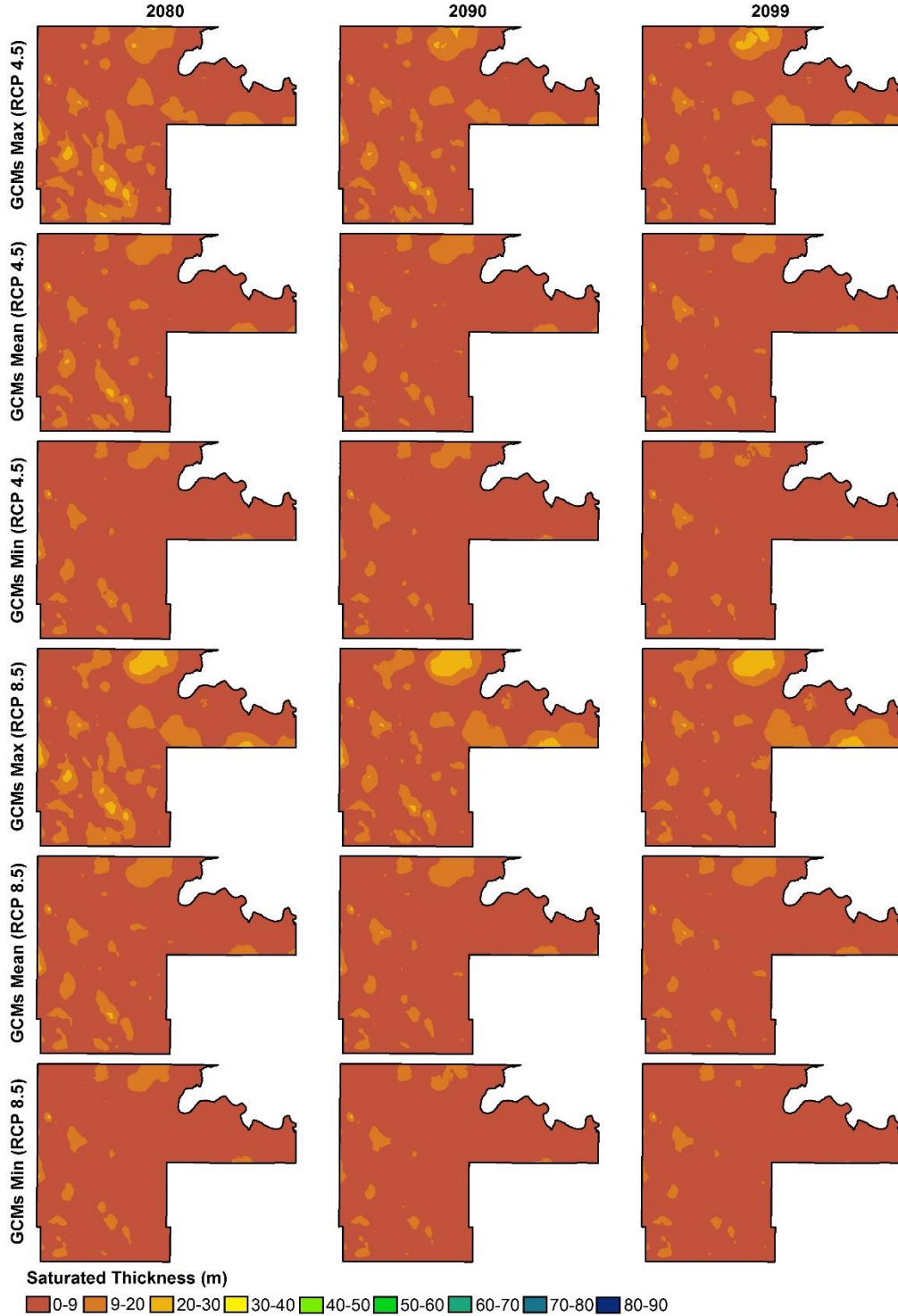


Figure A6. Gridded data of the minimum (GCMs Min), maximum (GCMs Max), and ensemble mean (GCMs Mean) of projected saturated thickness values in 2080, 2090, and 2099. Projected saturated thickness values are obtained through running the random forests (RF) model for various climate scenarios developed based on the downscaled climatic data of 20 global climate models (GCMs) for two different representative concentration pathways (RCP) scenarios, namely RCP 4.5 and RCP 8.5.

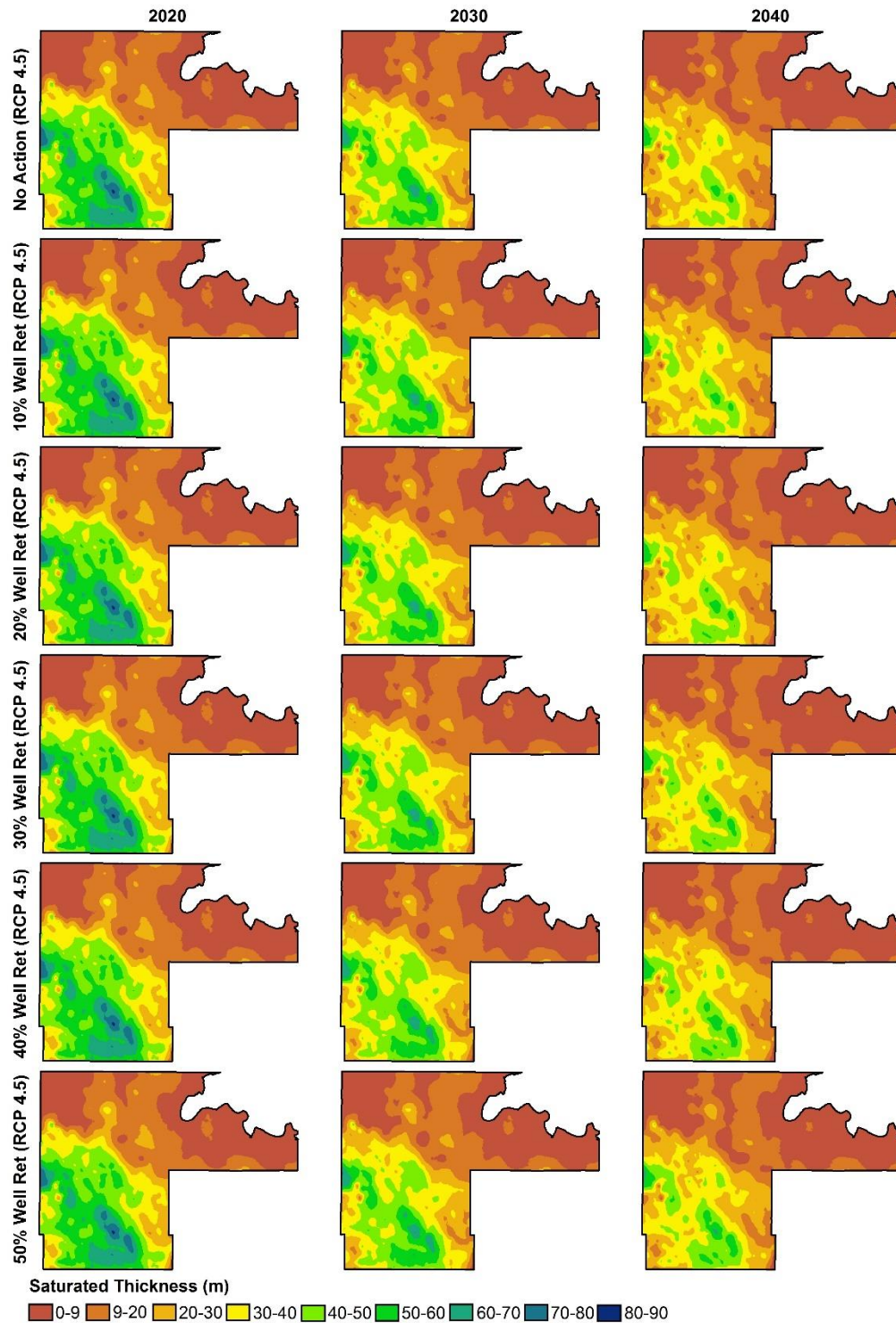


Figure A7. Gridded data of projected saturated thickness values obtained through running the random forests (RF) model for six well retirement plans (including the no-action scenario) and under the RCP 4.5 ensemble mean climate scenario in 2020, 2030, and 2040. The RCP 4.5 ensemble mean climate scenario is developed based on the ensemble mean of downscaled climate projections from 20 global climate models (GCMs) for representative concentration pathways (RCP) scenario 4.5.

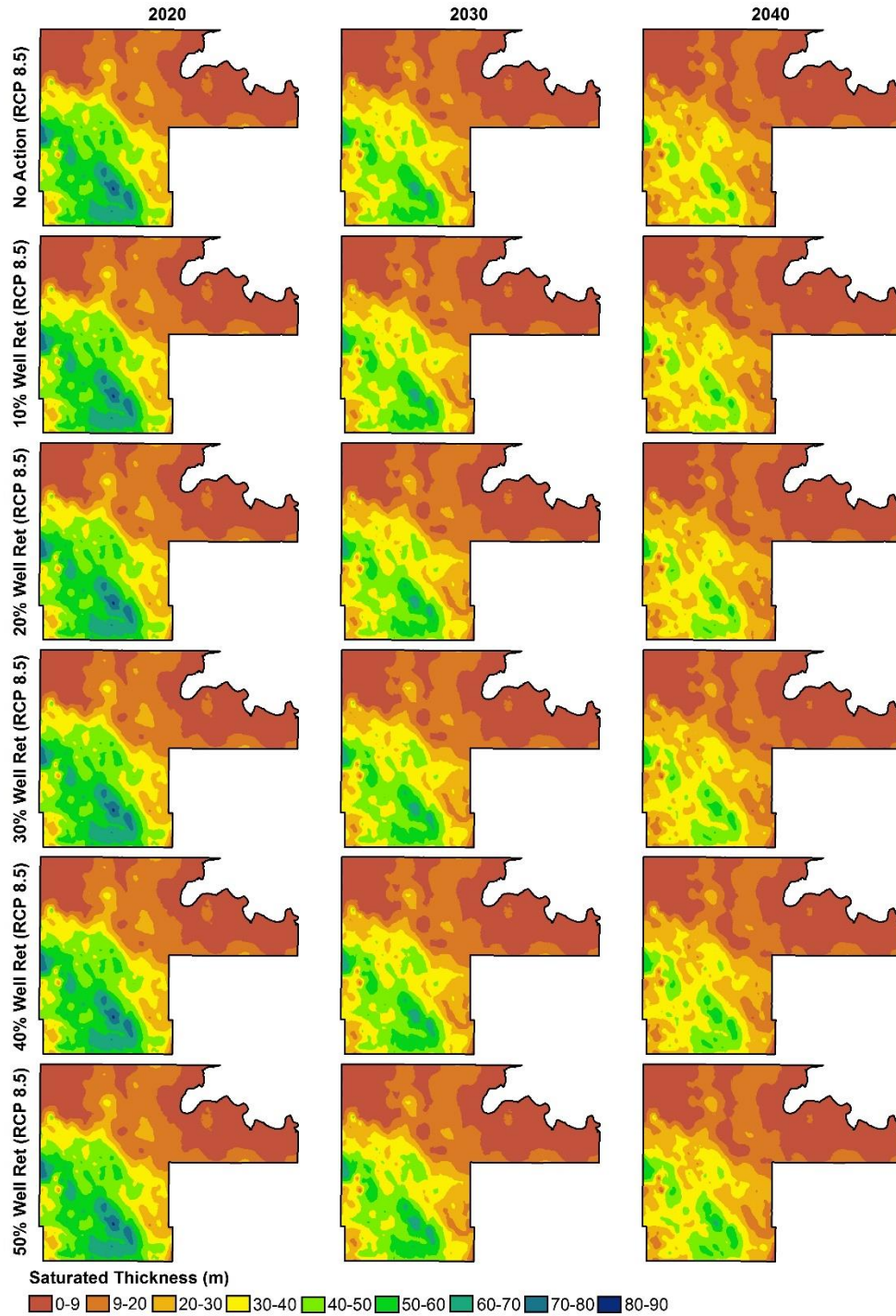


Figure A8. Gridded data of projected saturated thickness values obtained through running the random forests (RF) model for six well retirement plans (including the no-action scenario) and under the RCP 8.5 ensemble mean climate scenario in 2020, 2030, and 2040. The RCP 8.5 ensemble mean climate scenario is developed based on the ensemble mean of downscaled climate projections from 20 global climate models (GCMs) for representative concentration pathways (RCP) scenario 8.5.

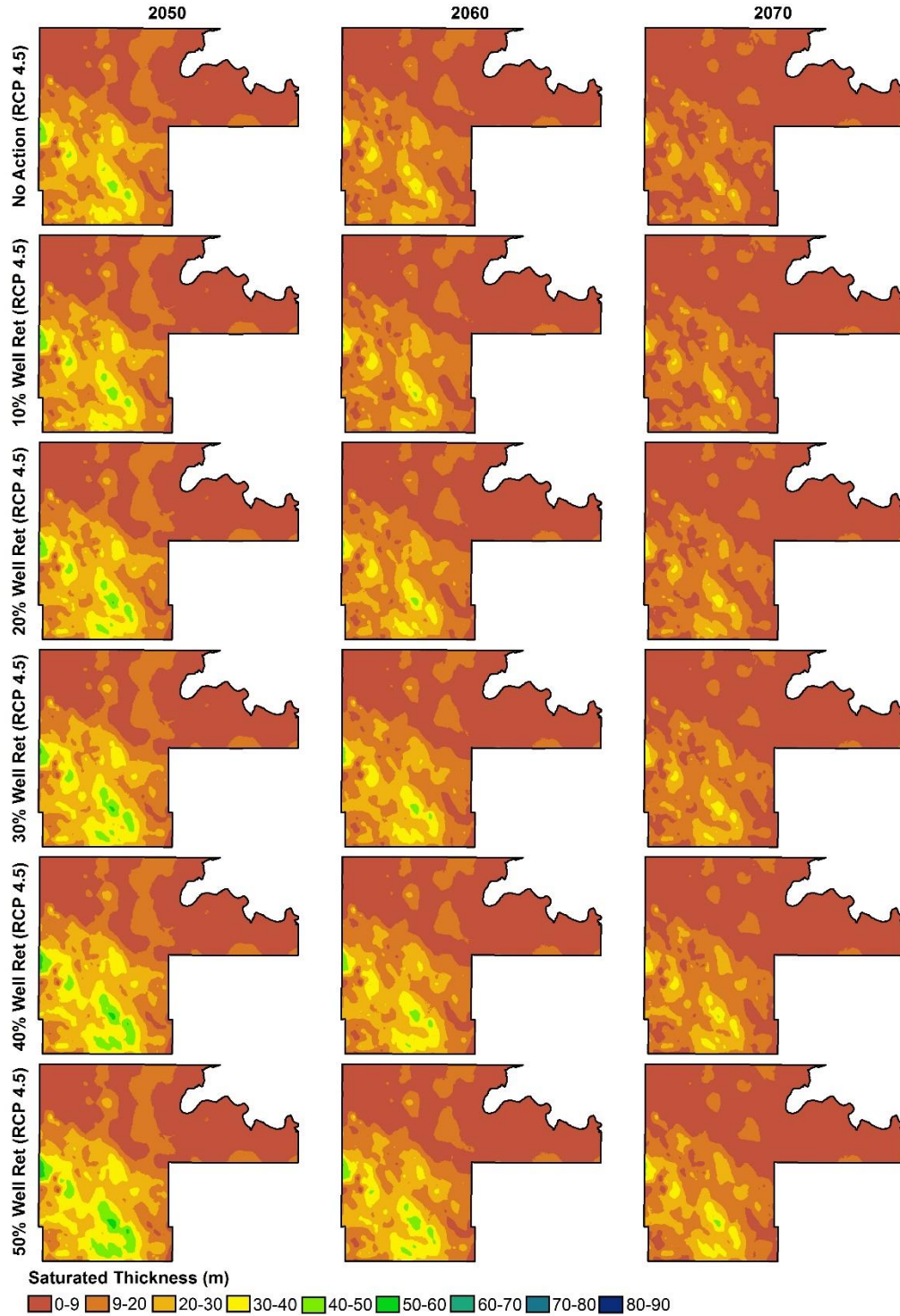


Figure A9. Gridded data of projected saturated thickness values obtained through running the random forests (RF) model for six well retirement plans (including the no-action scenario) and under the RCP 4.5 ensemble mean climate scenario in 2050, 2060, and 2070. The RCP 4.5 ensemble mean climate scenario is developed based on the ensemble mean of downscaled climate projections from 20 global climate models (GCMs) for representative concentration pathways (RCP) scenario 4.5.

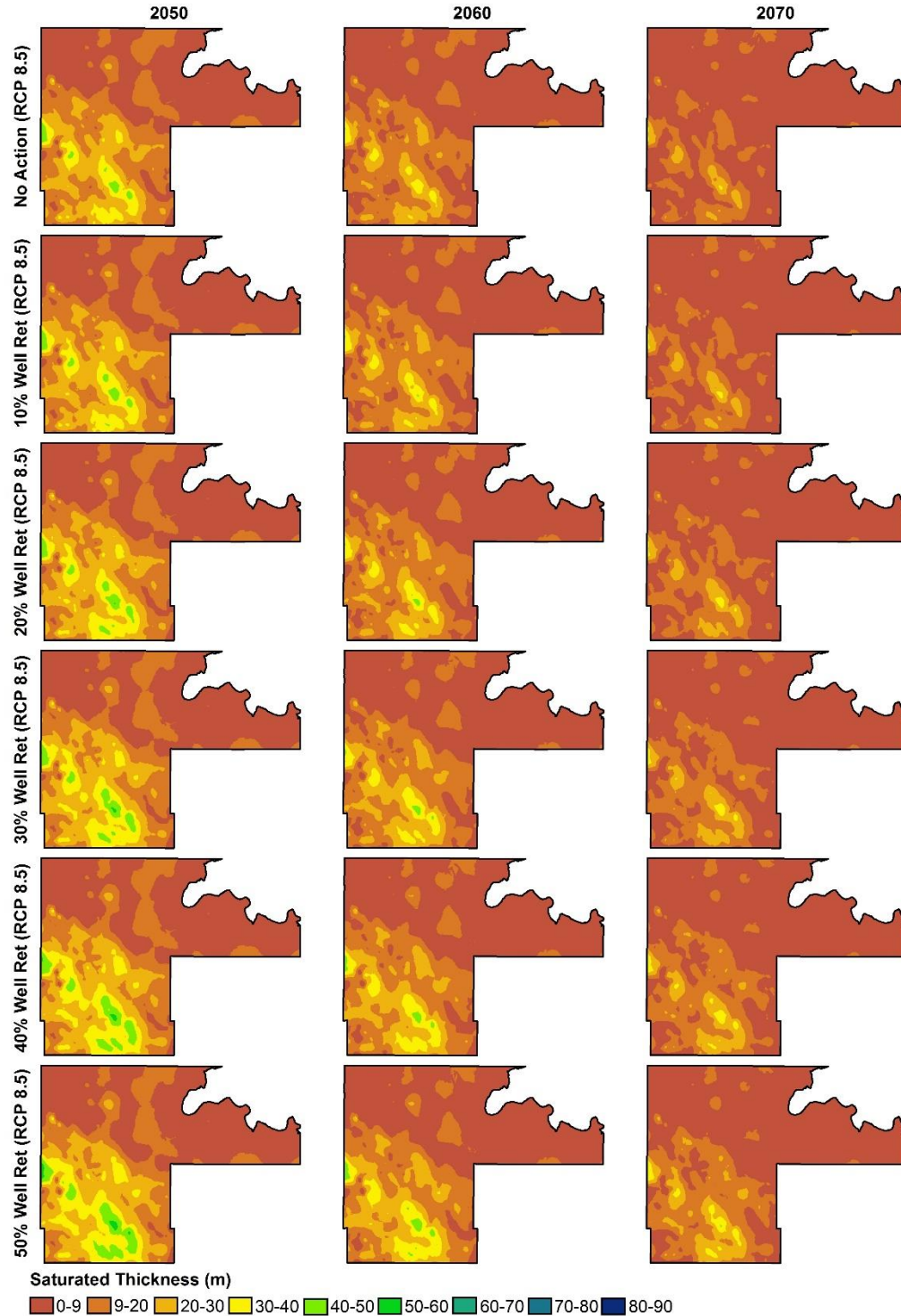


Figure A10. Gridded data of projected saturated thickness values obtained through running the random forests (RF) model for six well retirement plans (including the no-action scenario) and under the RCP 8.5 ensemble mean climate scenario in 2050, 2060, and 2070. The RCP 8.5 ensemble mean climate scenario is developed based on the ensemble mean of downscaled climate projections from 20 global climate models (GCMs) for representative concentration pathways (RCP) scenario 8.5.

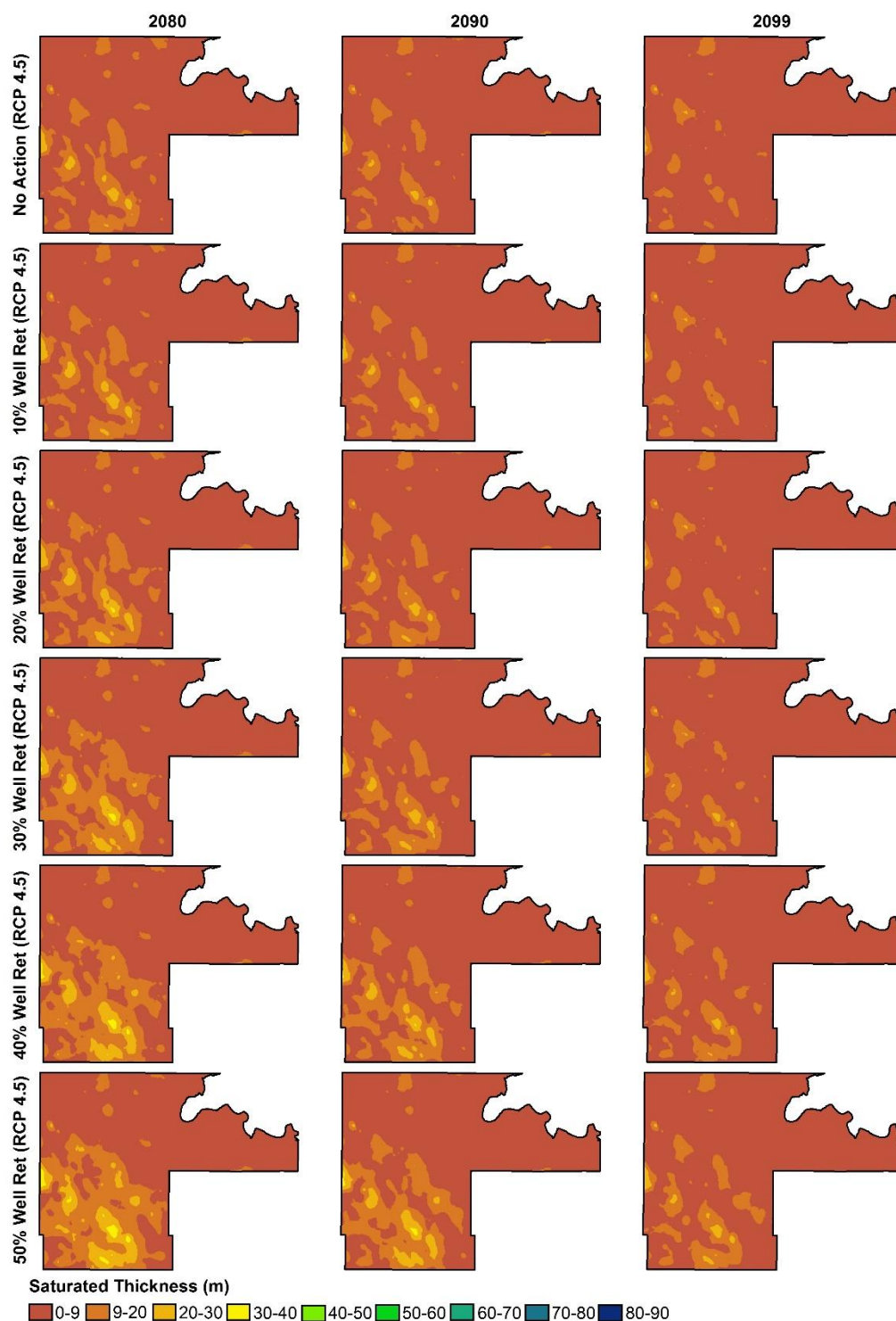


Figure A11. Gridded data of projected saturated thickness values obtained through running the random forests (RF) model for six well retirement plans (including the no-action scenario) and under the RCP 4.5 ensemble mean climate scenario in 2080, 2090, and 2099. The RCP 4.5 ensemble mean climate scenario is developed based on the ensemble mean of downscaled climate projections from 20 global climate models (GCMs) for representative concentration pathways (RCP) scenario 4.5.

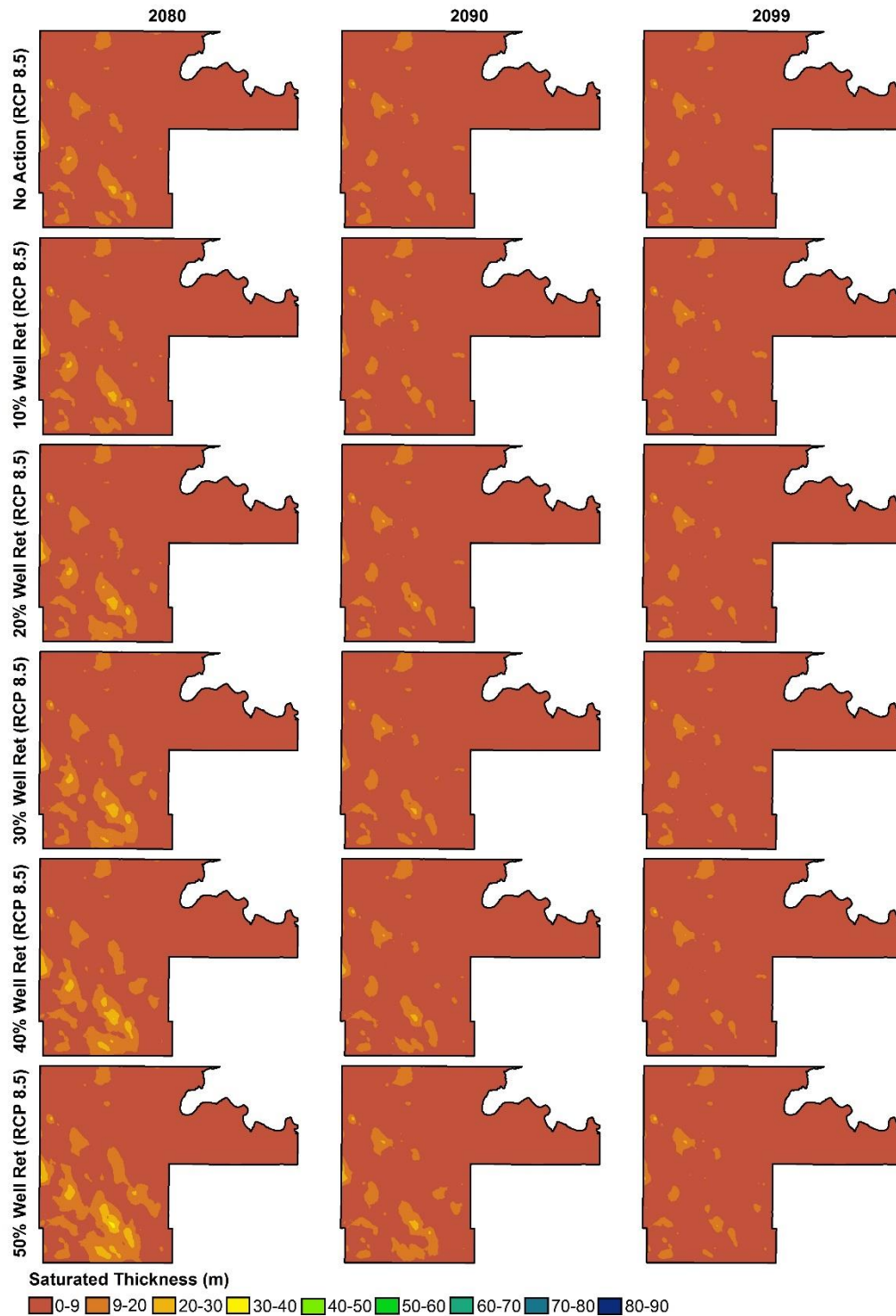


Figure A12. Gridded data of projected saturated thickness values obtained through running the random forests (RF) model for six well retirement plans (including the no-action scenario) and under the RCP 8.5 ensemble mean climate scenario in 2080, 2090, and 2099. The RCP 8.5 ensemble mean climate scenario is developed based on the ensemble mean of downscaled climate projections from 20 global climate models (GCMs) for representative concentration pathways (RCP) scenario 8.5.

Table A1. A list of all global climate models (GCMs) considered in the current study along with their resolution and corresponding institution

GCM Model	Institution	Resolution (Long $\times$ Lat)
BCC-CSM1-1	Beijing Climate Center, China Meteorological Administration, China	$2.8125^{\circ} \times 2.7906^{\circ}$
BCC-CSM1-1-m	Beijing Climate Center, China Meteorological Administration, China	$2.8125^{\circ} \times 2.7906^{\circ}$
BNU-ESM	Beijing Normal University, China	$2.8125^{\circ} \times 2.7906^{\circ}$
CanESM2	Canadian Center for Climate Modeling and Analysis, Canada	$2.8125^{\circ} \times 2.7906^{\circ}$
CCSM4	U.S. National Center for Atmospheric Research, U.S.	$1.25^{\circ} \times 0.9424^{\circ}$
CNRM-CM5	Centre National de Recherches Meteorologiques and Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique, France	$1.40625^{\circ} \times 1.4008^{\circ}$
CSIRO-Mk3-6-0	Queensland Climate Change Centre of Excellence and Commonwealth Scientific and Industrial Research Organisation, Australia	$1.875^{\circ} \times 1.8653^{\circ}$
GFDL-ESM2G	NOAA Geophysical Fluid Dynamics Laboratory, U.S.	$2.5^{\circ} \times 2.0225^{\circ}$
GFDL-ESM2M	NOAA Geophysical Fluid Dynamics Laboratory, U.S.	$2.5^{\circ} \times 2.0225^{\circ}$
HadGEM2-CC365	U.K. Met Office Hadley Centre, U.K.	$1.875^{\circ} \times 1.25^{\circ}$
HadGEM2-ES365	U.K. Met Office Hadley Centre, U.K.	$1.875^{\circ} \times 1.25^{\circ}$
INM-CM4	Russian Institute for Numerical Mathematics, Russia	$2.0^{\circ} \times 1.5^{\circ}$
IPSL-CM5A-LR	Institut Pierre Simon Laplace, France	$3.75^{\circ} \times 1.8947^{\circ}$
IPSL-CM5A-MR	Institut Pierre Simon Laplace, France	$2.5^{\circ} \times 1.2676^{\circ}$
IPSL-CM5B-LR	Institut Pierre Simon Laplace, France	$3.75^{\circ} \times 1.8947^{\circ}$
MIROC5	University of Tokyo, National Institute for Environmental Studies and Japan Agency for Marine-Earth Science and Technology, Japan	$1.40625^{\circ} \times 1.4008^{\circ}$
MIROC-ESM	University of Tokyo, National Institute for Environmental Studies and Japan Agency for Marine-Earth Science and Technology, Japan	$2.8125^{\circ} \times 2.7906^{\circ}$
MIROC-ESM-CHEM	University of Tokyo, National Institute for Environmental Studies and Japan Agency for Marine-Earth Science and Technology, Japan	$2.8125^{\circ} \times 2.7906^{\circ}$
MRI-CGCM3	Meteorological Research Institute, Japan	$1.125^{\circ} \times 1.12148^{\circ}$
NorESM1-M	Norwegian Climate Center, Norway	$2.5^{\circ} \times 1.8947^{\circ}$

APPENDIX B

SUPPORTING INFORMATION FOR CHAPTER 4. CAPTURING HUMAN-CROP- GROUNDWATER INTERACTIONS: MODELING REAL-WORLD AGENTS IN AN INTENSIVELY IRRIGATED REGION OF THE U.S. HIGH PLAINS

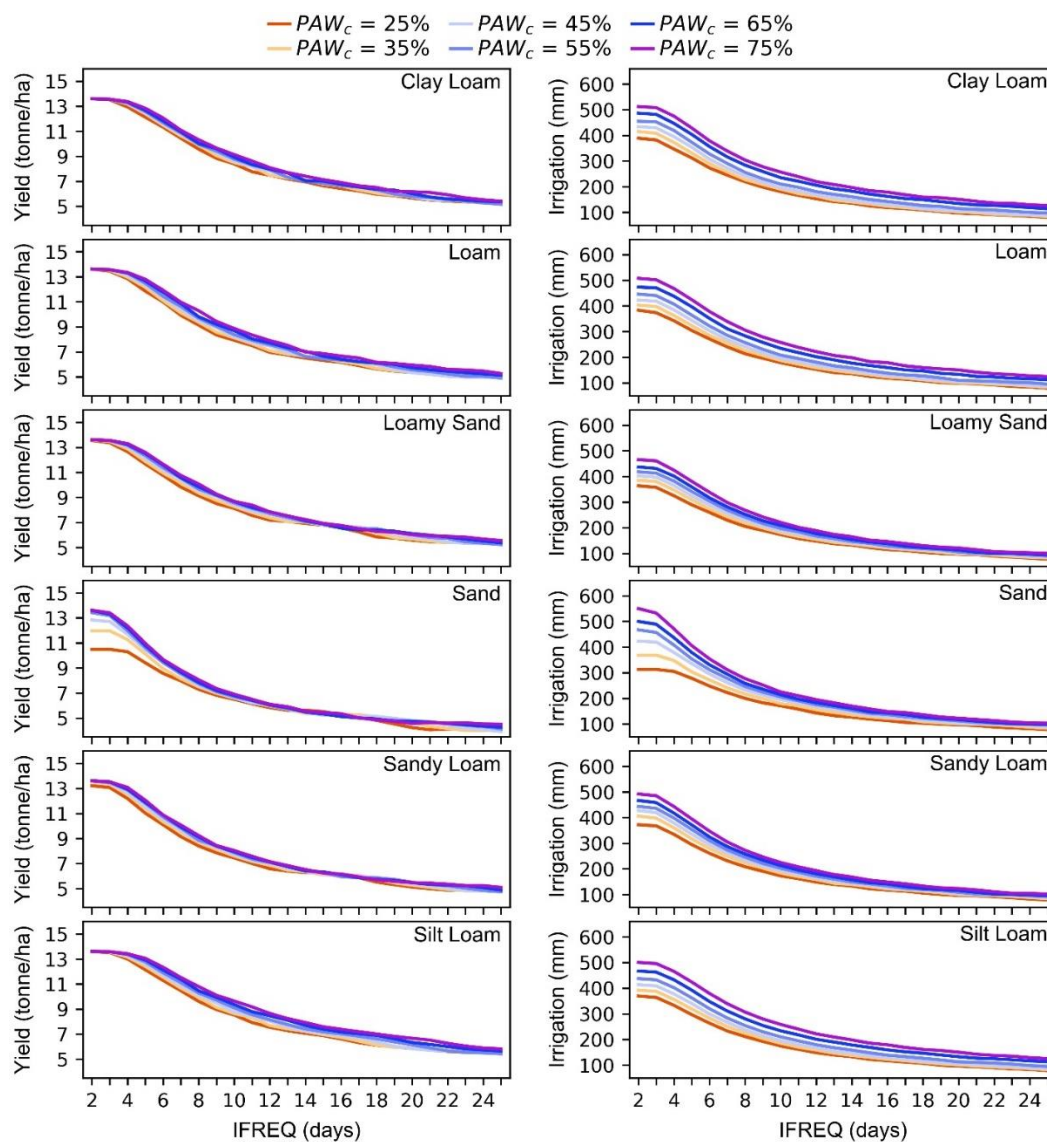


Figure B1. Corn yield and seasonal irrigation use across different generalized soil categories, influenced by varying critical plant available water (PAW_c) and irrigation frequency (IFREQ) values, estimated by DSSAT. Data averaged across different soil subtypes and weather conditions from 1981 to 2019. Note: 1 tonne/ha of corn is equal to 15.93 bu/ac and 1 mm to 0.039 in.

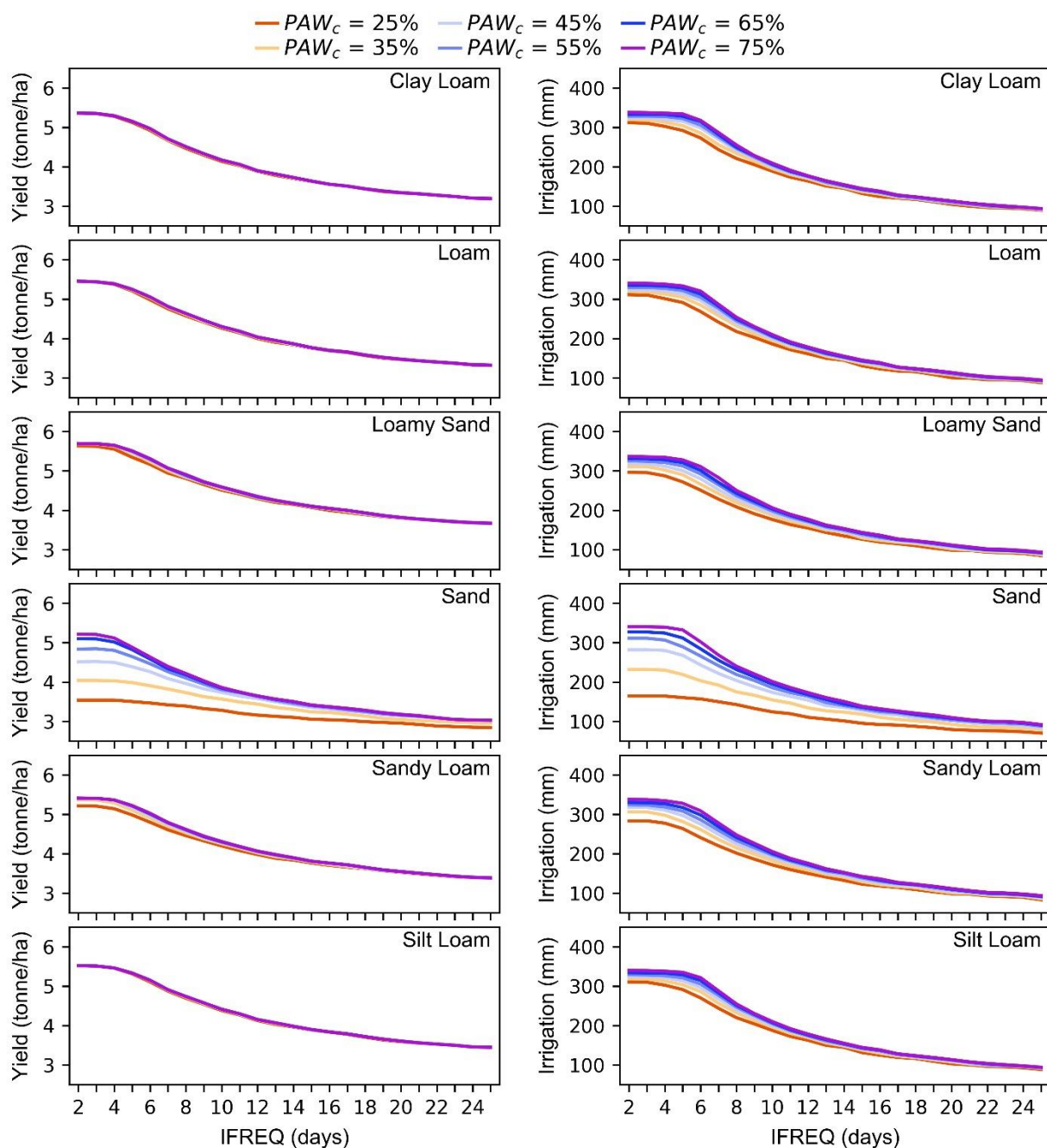


Figure B2. Winter wheat yield and seasonal irrigation use across different generalized soil categories, influenced by varying critical plant available water (PAW_c) and irrigation frequency (IFREQ) values, estimated by DSSAT. Data averaged across different soil subtypes and weather conditions from 1981 to 2019. Note: 1 tonne/ha of winter wheat is equal to 14.87 bu/ac and 1 mm to 0.039 in.

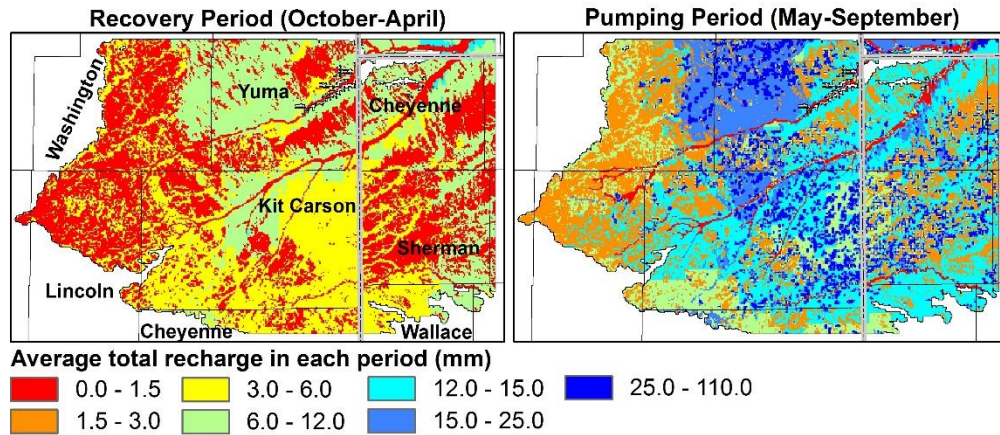


Figure B3. Average recharge during the recovery and pumping stress periods from 1984 to 2018, as computed by the ABM-MODFLOW model. Note: 1 mm is equal to 0.039 in.

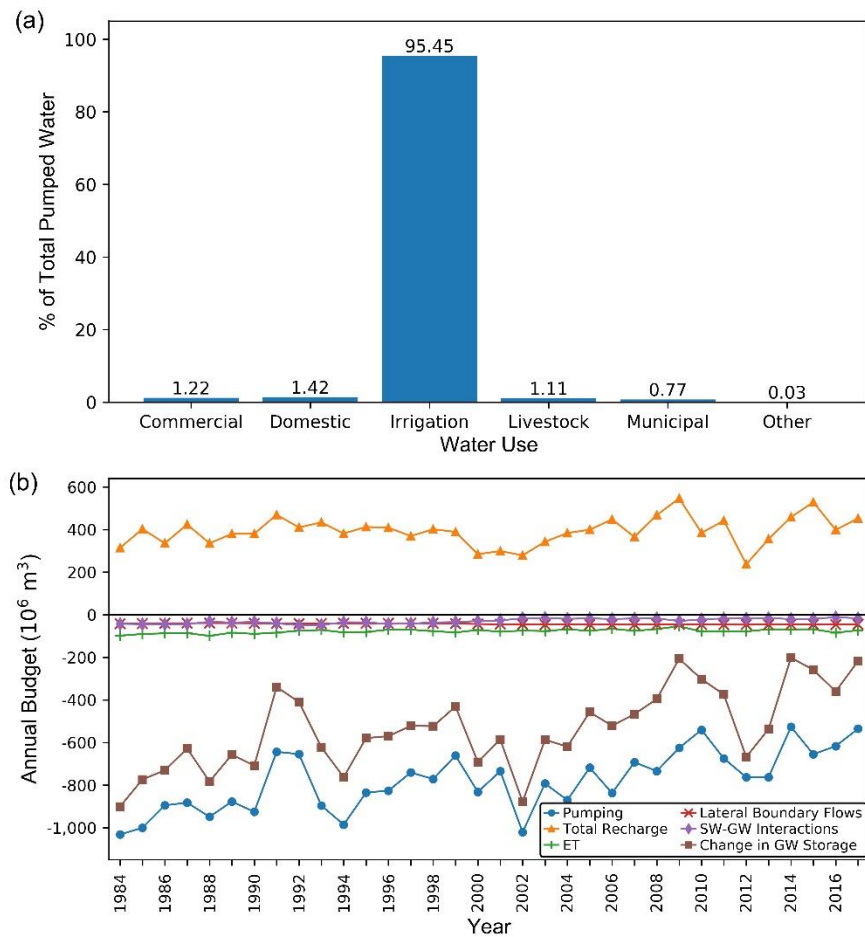


Figure B4. (a) Percentage breakdown of total groundwater extraction for different purposes from 1984 to 2018 in the ABM-MODFLOW model. (b) Annual groundwater budget (SW and GW: surface water and groundwater) in the ABM-MODFLOW model. Note: 106 m³ is equal to 810.71 ac-ft.

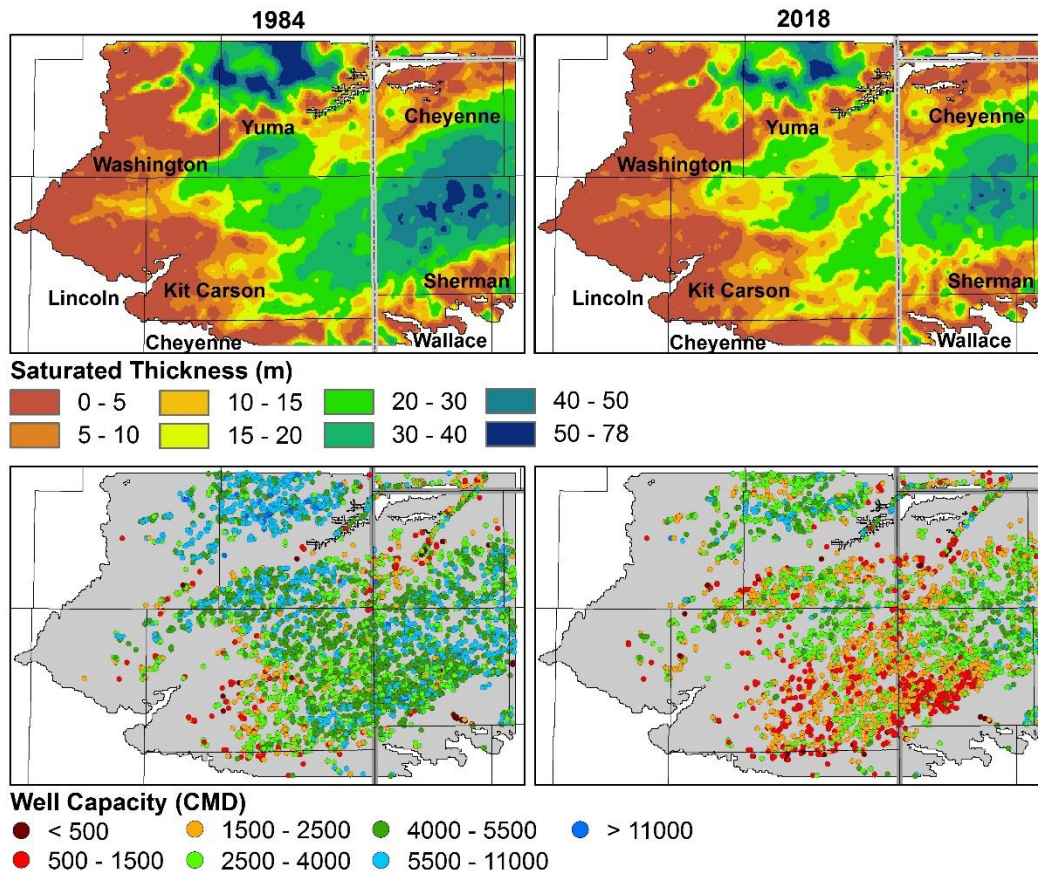


Figure B5. Aquifer saturated thickness and well capacities for active irrigation wells at the beginning (left panel) and end (right panel) of the ABM-MODFLOW simulation period. Note: 1 m is equal to 3.28 ft and 1 CMD (cubic meters per day) to 0.1835 GPM (gallons per minute).

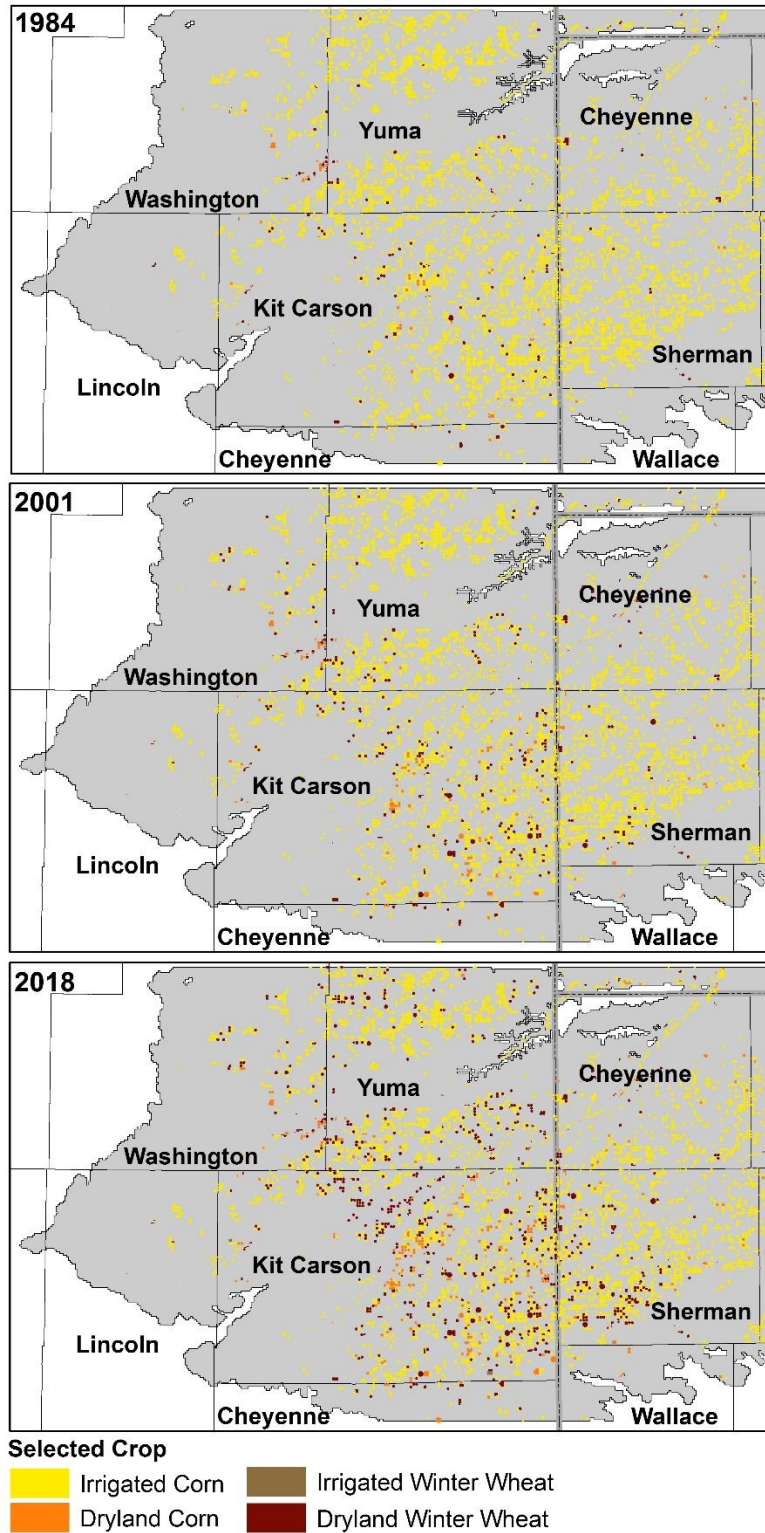


Figure B6. Agents' crop choice in 1984, 2001, and 2018, as determined by the ABM-MODFLOW model.

Table B1. Calibrated cultivar coefficients specified for corn and winter wheat in the agronomic model (DSSAT).

Parameter	Definition	Corn	Winter Wheat
P1	Thermal time from seedling emergence to the end of the juvenile phase during which the plant is not responsive to changes in photoperiod (°C days).	265	-
P1V	Days at the optimum vernalization temperature required to complete vernalization.	-	45
P1D	Percentage reduction in development when photoperiod is 10 hours shorter than the threshold, which is considered to be 20 hours, relative to that at the threshold.	-	50
P2	Extent to which development is delayed for each hour increase in photoperiod above the longest photoperiod at which development is at maximum rate, which is considered to be 12.5 hours (days).	0.4	-
P5	Thermal time from silking to physiological maturity (corn; °C days) or grain filling phase duration (winter wheat; °C days).	589	630
G1	Kernel number per unit canopy weight at anthesis (#/g).	-	21
G2	Maximum possible number of kernels per plant (corn; #) or standard kernel size under optimum conditions (winter wheat; mg).	908	25
G3	Kernel filling rate during the linear grain filling stage and under optimum conditions (corn; mg/day) or standard and non-stressed dry weight of a single tiller at maturity (winter wheat; g).	10	2
PHINT	Phylochron interval (°C days).	45	70

Source of data for corn is DeJonge et al. (2011) and for winter wheat is Elsayed et al. (2019).

Table B2. Management parameters considered for corn and winter wheat production.

Parameter	Corn	Winter Wheat
Conditions at Planting		
Planting Date	May 1	September 15
Planting Depth (cm)	5	5
Seeding Rate – Dryland (seeds/ha)	37,000	1,730,000
Seeding Rate – Irrigated (seeds/ha)	84,000	2,965,000
Seed Emergence (%)		95
Initial plant available water (soil water content above wilting point) (cm/cm)		0.13
Simulation Options		
Irrigation Application Depth (mm)		25
Irrigation Efficiency (%)		85
Irrigation Management Depth (cm)		60
IFREQ (days)	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, and 25	
PAW _c (% of PAW)	25, 35, 45, 55, 65, and 75	
Reference Evapotranspiration Method	FAO Penman-Monteith equation (Allen et al., 1998)	

Table B3. Economic model inputs.

Crop	Price (USD/tonne)*	Fixed Production Costs (USD/ha)**	Pumping Costs (USD/m ³)***
Irrigated Corn	182.79	910.56	0.03
Dryland Corn	182.79	443.95	0.00
Irrigated Winter Wheat	209.84	365.49	0.03
Dryland Winter Wheat	209.84	279.13	0.00

* Crop prices used here are the average of the 2010-2019 period to exclude the extreme volatility in crop prices experienced from 2007 to 2009.

** Costs are estimated based on the 2021 farm budgets (Kansas State University, 2021). Land rental and machinery ownership expenses are excluded from the calculations. Using the Farm Income and Wealth Statistics (Economic Research Service, 2021), the average government payment for each crop from 2010 to 2018 is estimated and included as a subtrahend in the calculation of fixed production costs.

*** Including energy cost (computed using a well depth of 91 m and the average natural gas price from 2010 to 2019) plus repair costs in 2021 (Kansas State University, 2021).

Note. 1 tonne of corn is equal to 39.37 bu, 1 tonne of winter wheat to 36.74 bu, 1 ha to 2.47 ac, and 1 m³ to 0.0097 ac-in.

APPENDIX C

SUPPORTING INFORMATION FOR CHAPTER 5. GROUNDWATER

CONSERVATION IN THE FACE OF CLIMATE CHANGE: DYNAMIC HUMAN-CROP- GROUNDWATER INTERACTIONS IN SEMI-ARID REGIONS

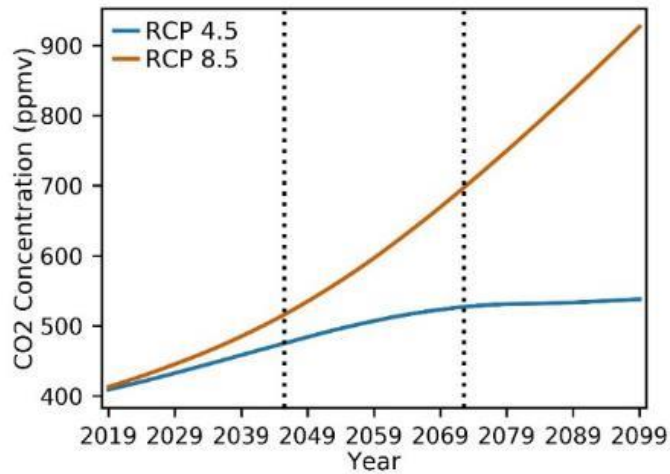


Figure C1. Projected annual atmospheric carbon dioxide concentrations (CO₂) for two representative concentration pathways (RCPs), RCP4.5 and RCP8.5. Dotted lines mark three 27-year intervals, dividing the entire projection into short-term (2019-2045), mid-term (2046-2072), and long-term periods (2073-2099).

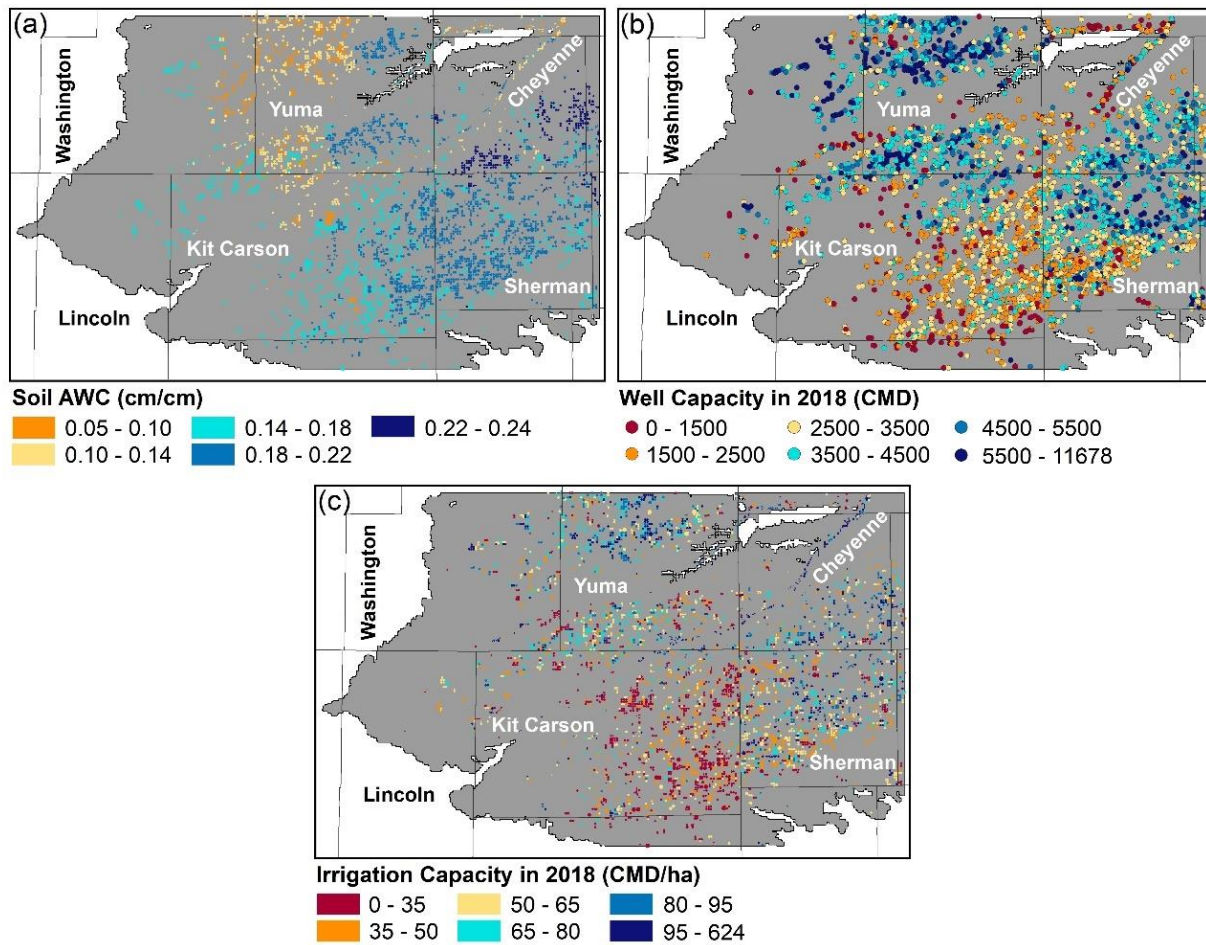


Figure C2. Attributes of agents. (a) Dominant Soil's available water capacity (AWC). (b) Well capacities in 2018. (c) Irrigation capacities in 2018. CMD stands for cubic meters per day.

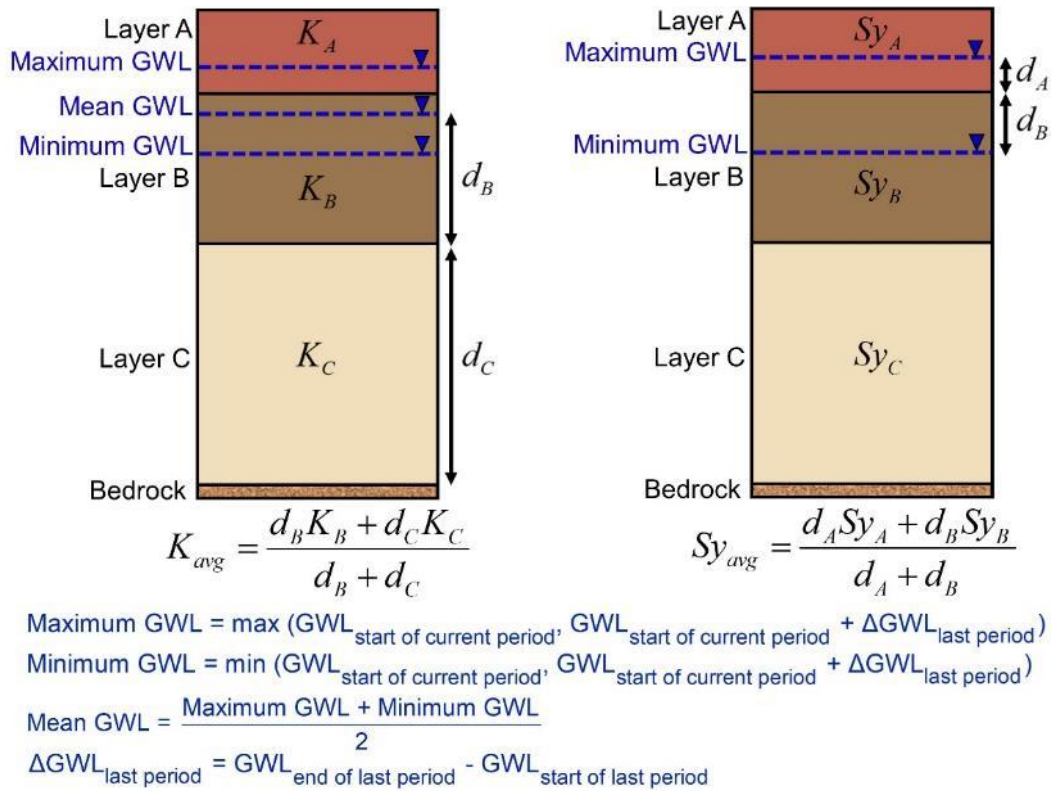


Figure C3. Graphical illustration of calculating weighted average horizontal hydraulic conductivity (K) and specific yield (Sy) with respect to groundwater levels (GWLs) in a given borehole at the start of each period (decade). For these calculations, we assume that the groundwater level change (ΔGWL) in the upcoming period will be identical to that of the preceding period.

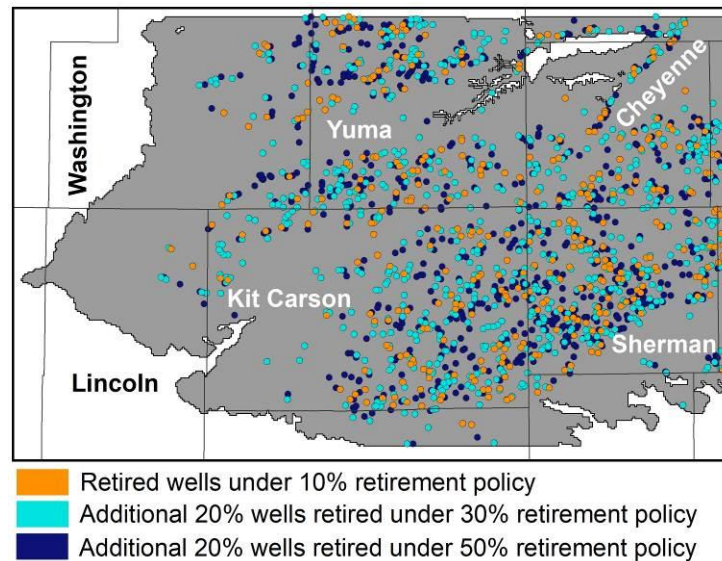


Figure C4. Distribution of retired wells under various levels of the irrigation well retirement policy.

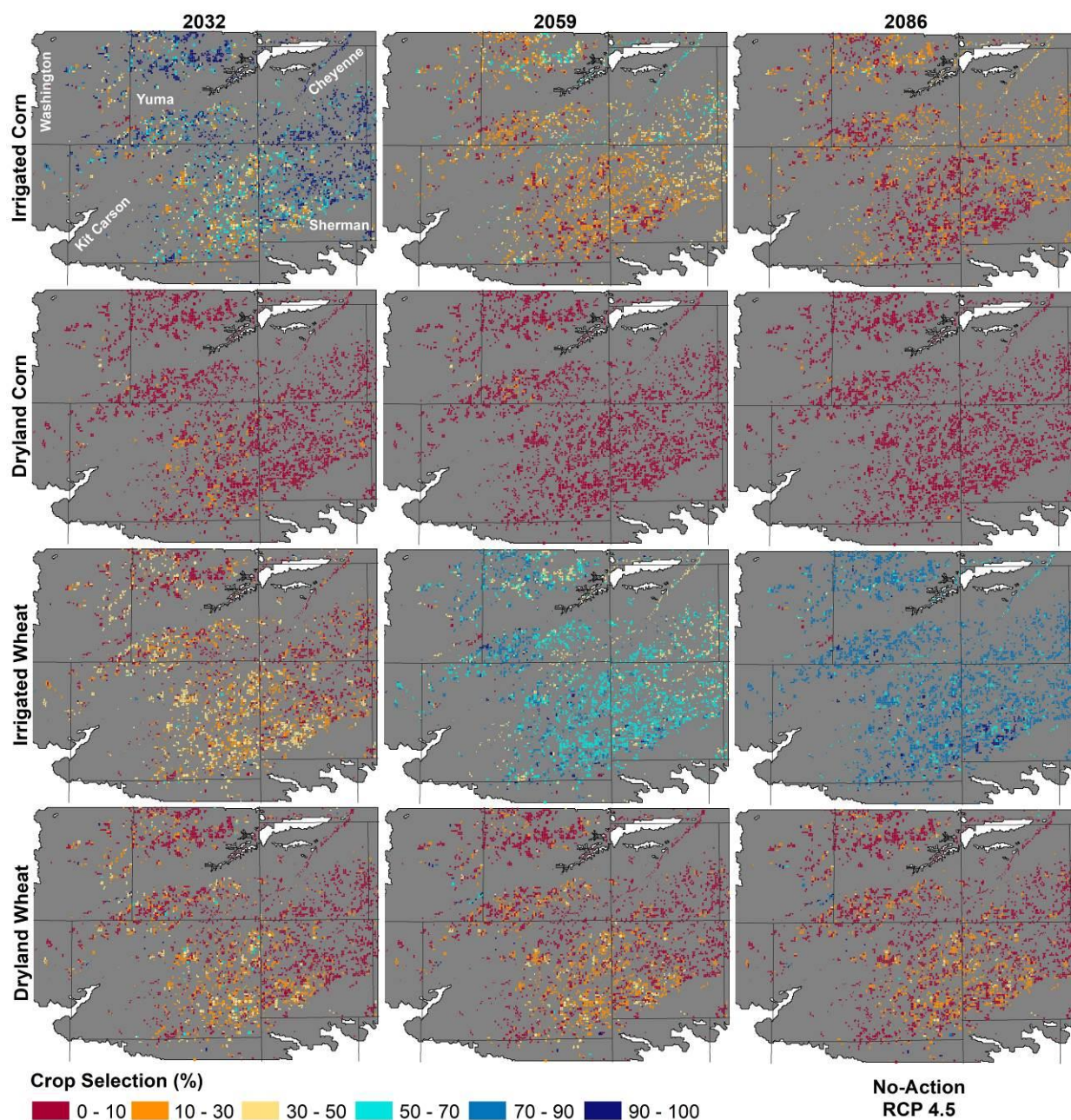


Figure C5. Percentages of selected crops on farms across the study area for the years 2032, 2059, and 2086. The displayed values are ensemble means derived from the ABM-MODFLOW simulations under an ensemble of climate projections for RCP4.5 and the no-action management scenario. These three years are the median years of short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).

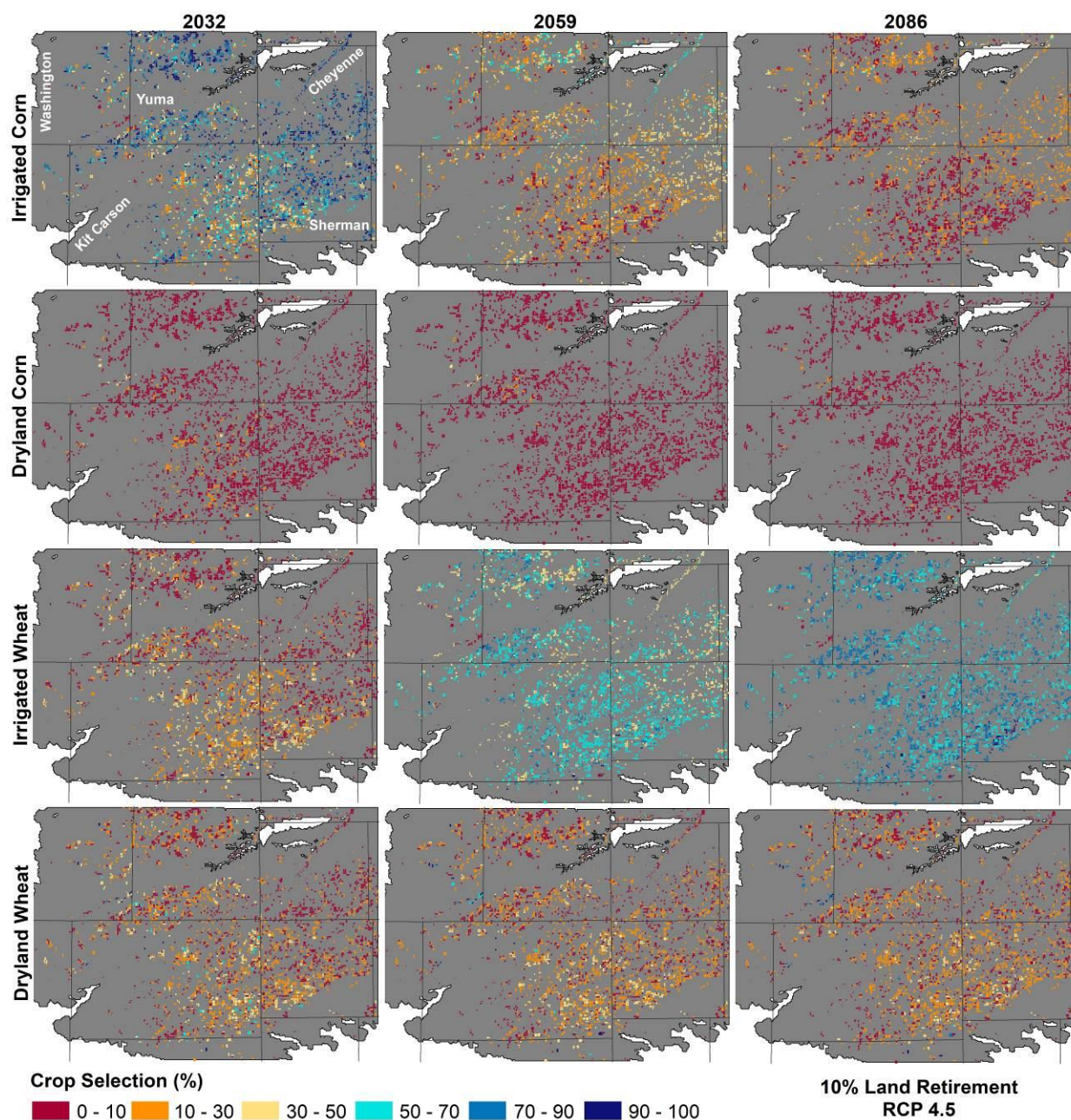


Figure C6. Percentages of selected crops on farms across the study area for the years 2032, 2059, and 2086. The displayed values are ensemble means derived from the ABM-MODFLOW simulations under an ensemble of climate projections for RCP4.5 and the 10% irrigated land retirement policy. These three years are the median years of short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).

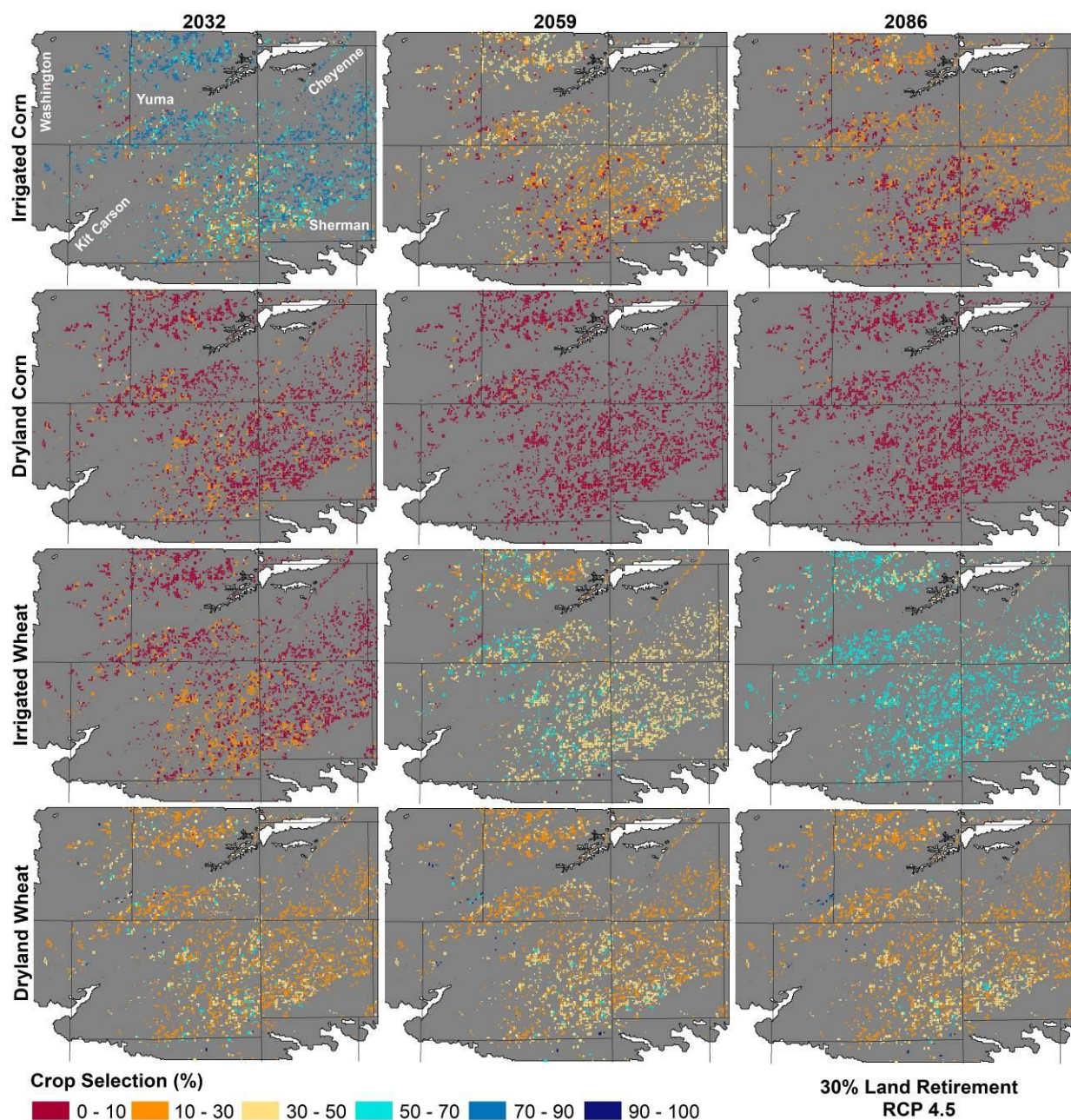


Figure C7. Percentages of selected crops on farms across the study area for the years 2032, 2059, and 2086. The displayed values are ensemble means derived from the ABM-MODFLOW simulations under an ensemble of climate projections for RCP4.5 and the 30% irrigated land retirement policy. These three years are the median years of short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).

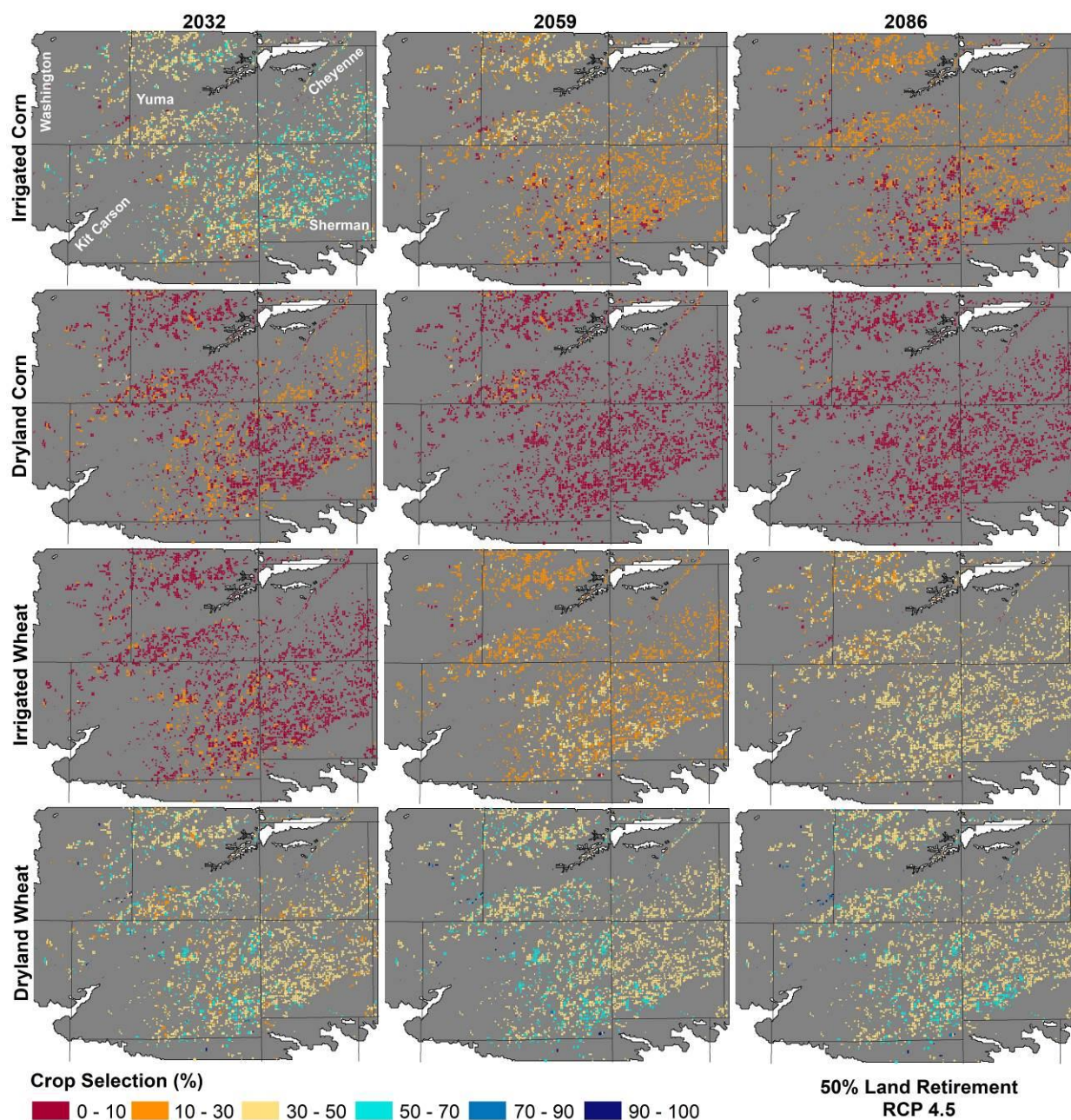


Figure C8. Percentages of selected crops on farms across the study area for the years 2032, 2059, and 2086. The displayed values are ensemble means derived from the ABM-MODFLOW simulations under an ensemble of climate projections for RCP4.5 and the 50% irrigated land retirement policy. These three years are the median years of short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).

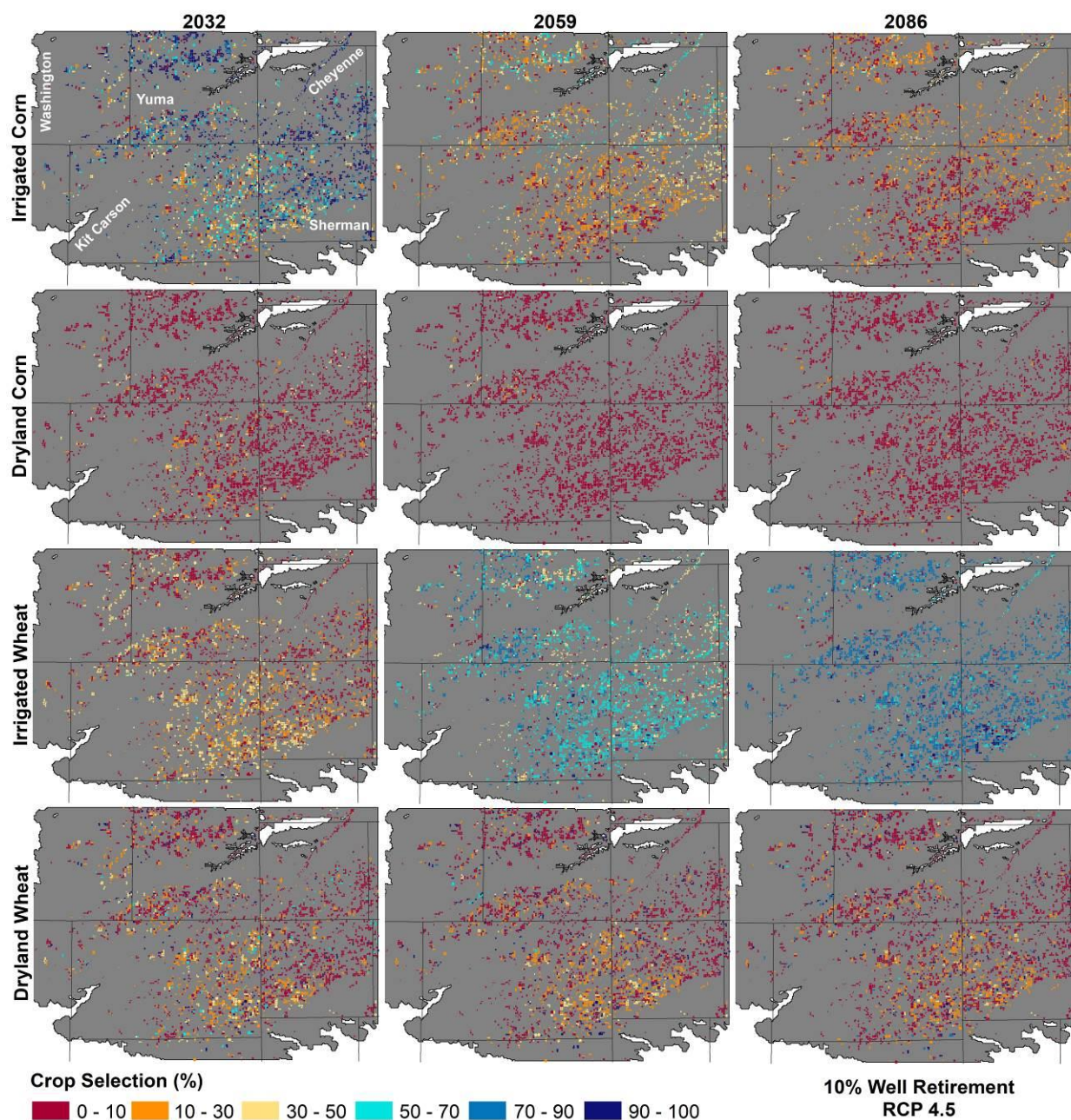


Figure C9. Percentages of selected crops on farms across the study area for the years 2032, 2059, and 2086. The displayed values are ensemble means derived from the ABM-MODFLOW simulations under an ensemble of climate projections for RCP4.5 and the 10% irrigation well retirement policy. These three years are the median years of short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).

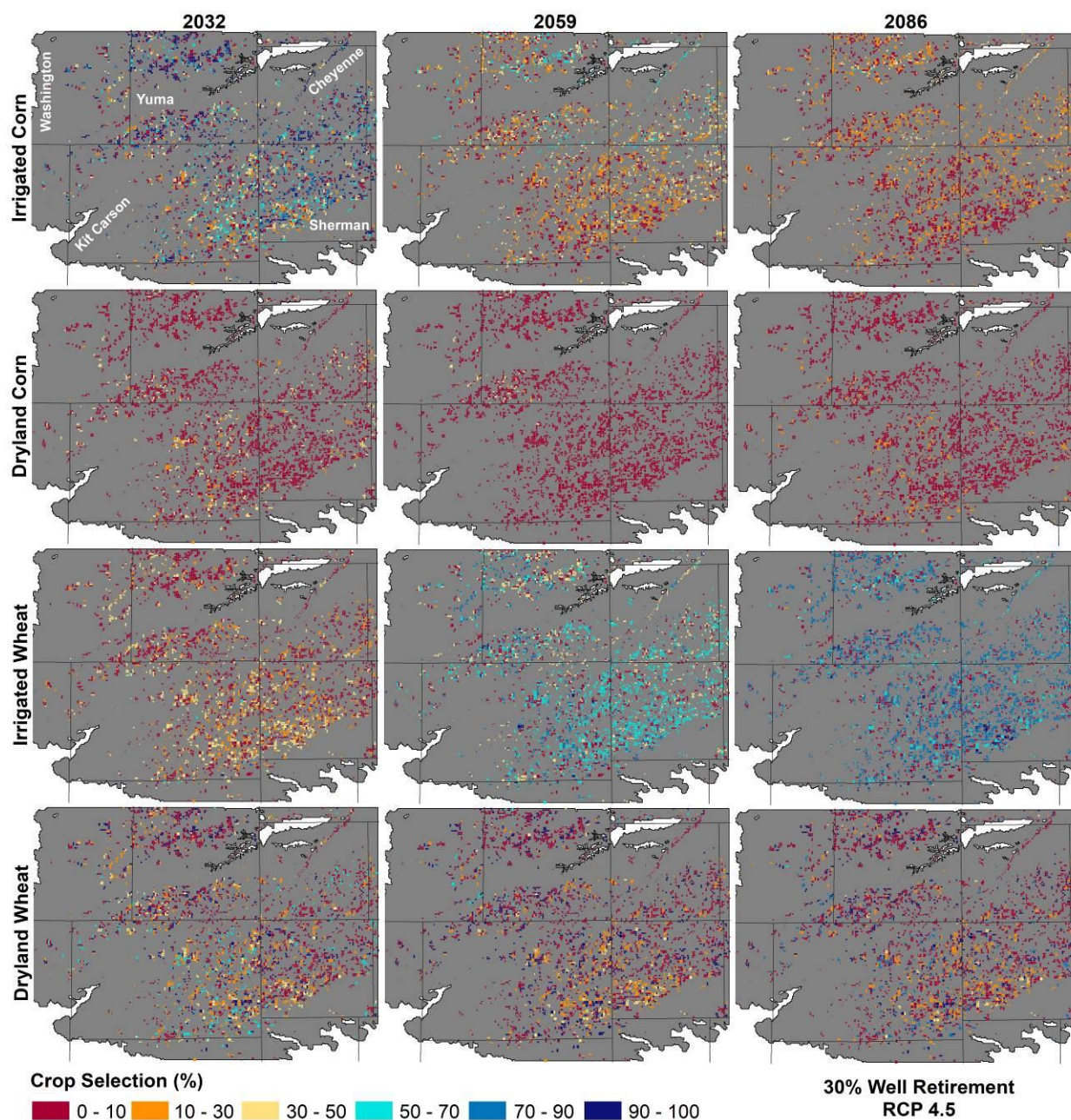


Figure C10. Percentages of selected crops on farms across the study area for the years 2032, 2059, and 2086. The displayed values are ensemble means derived from the ABM-MODFLOW simulations under an ensemble of climate projections for RCP4.5 and the 30% irrigation well retirement policy. These three years are the median years of short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).

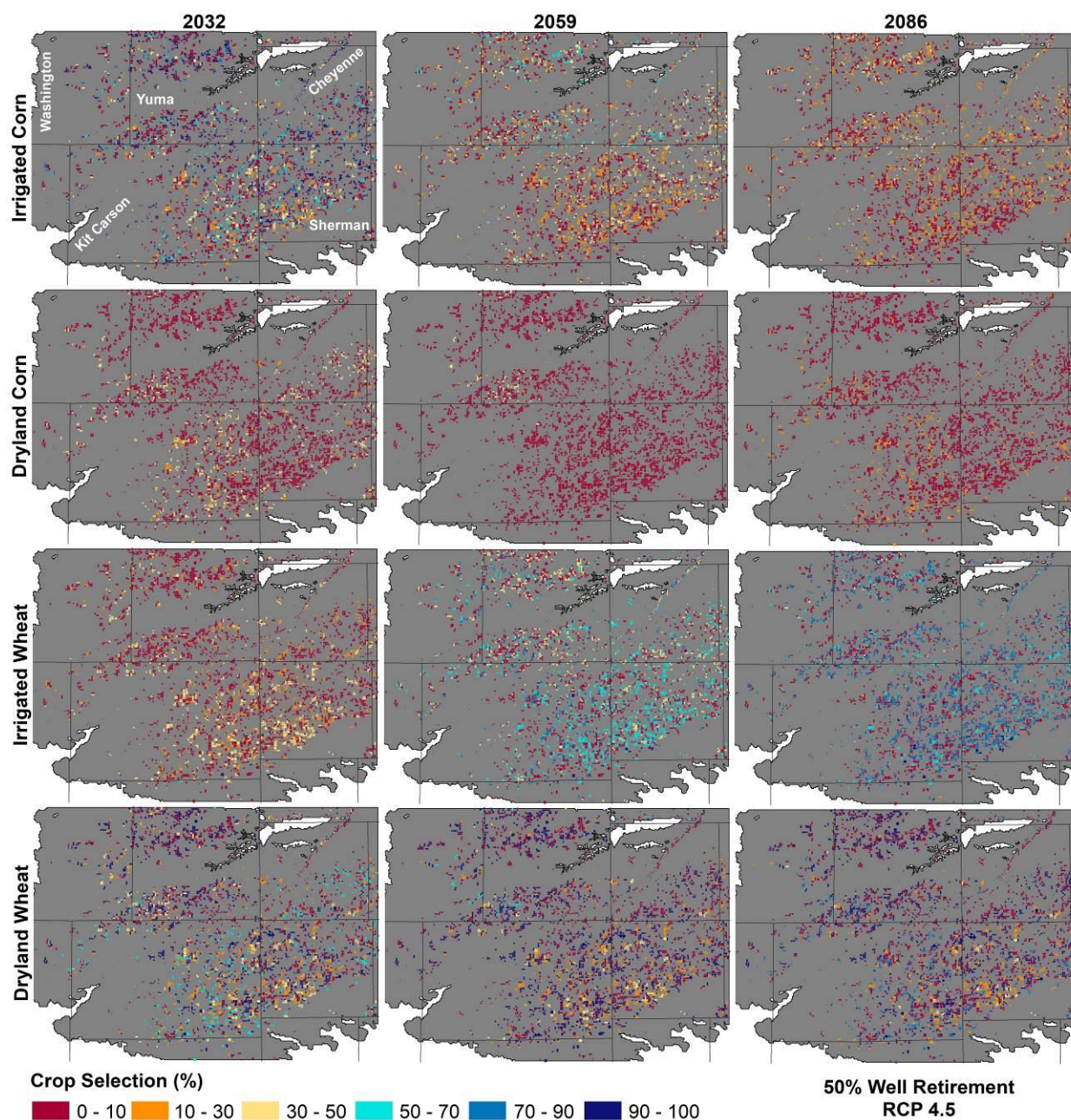


Figure C11. Percentages of selected crops on farms across the study area for the years 2032, 2059, and 2086. The displayed values are ensemble means derived from the ABM-MODFLOW simulations under an ensemble of climate projections for RCP4.5 and the 50% irrigation well retirement policy. These three years are the median years of short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).

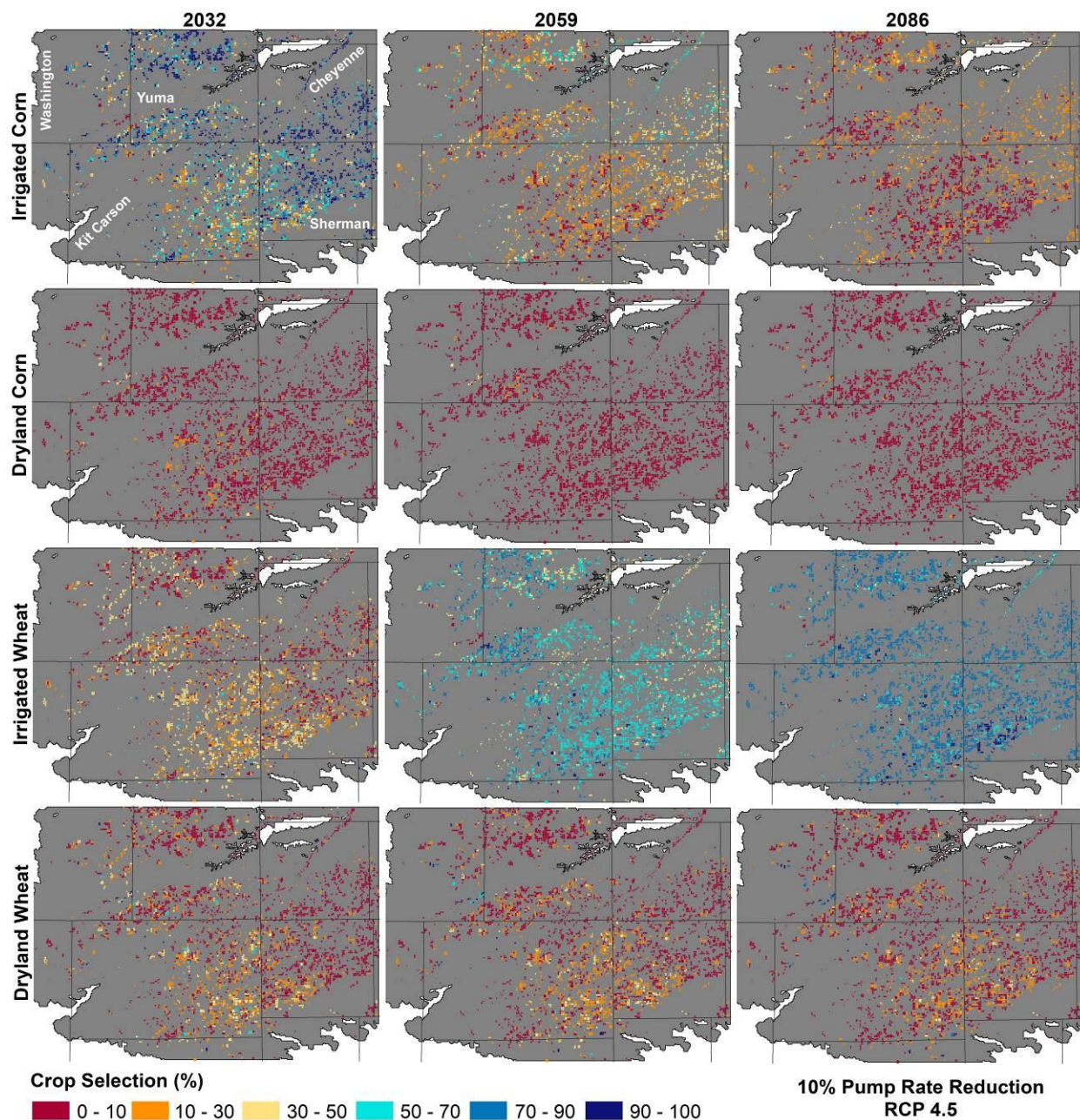


Figure C12. Percentages of selected crops on farms across the study area for the years 2032, 2059, and 2086. The displayed values are ensemble means derived from the ABM-MODFLOW simulations under an ensemble of climate projections for RCP4.5 and the 10% authorized pump rate reduction policy. These three years are the median years of short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).

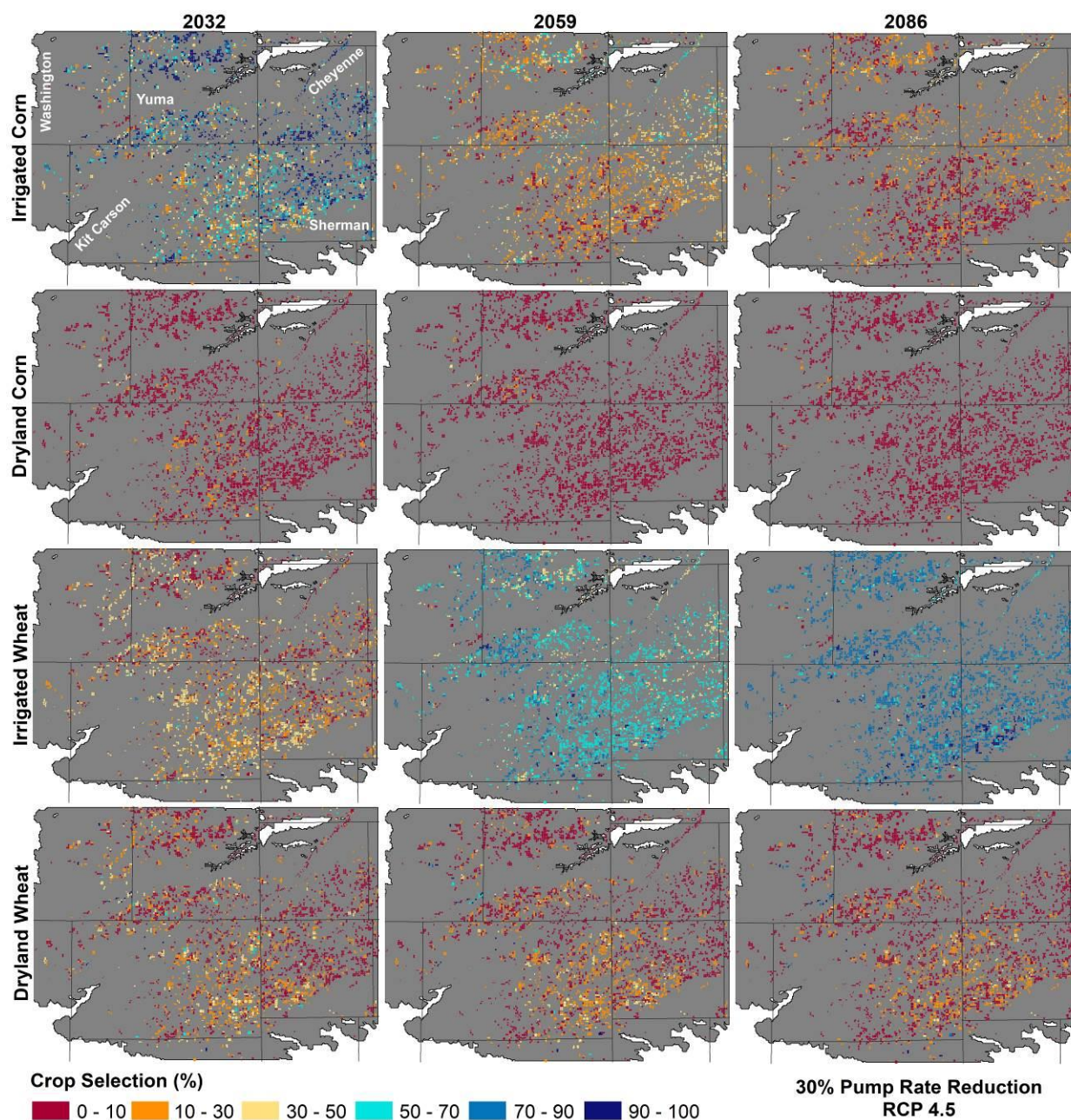


Figure C13. Percentages of selected crops on farms across the study area for the years 2032, 2059, and 2086. The displayed values are ensemble means derived from the ABM-MODFLOW simulations under an ensemble of climate projections for RCP4.5 and the 30% authorized pump rate reduction policy. These three years are the median years of short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).

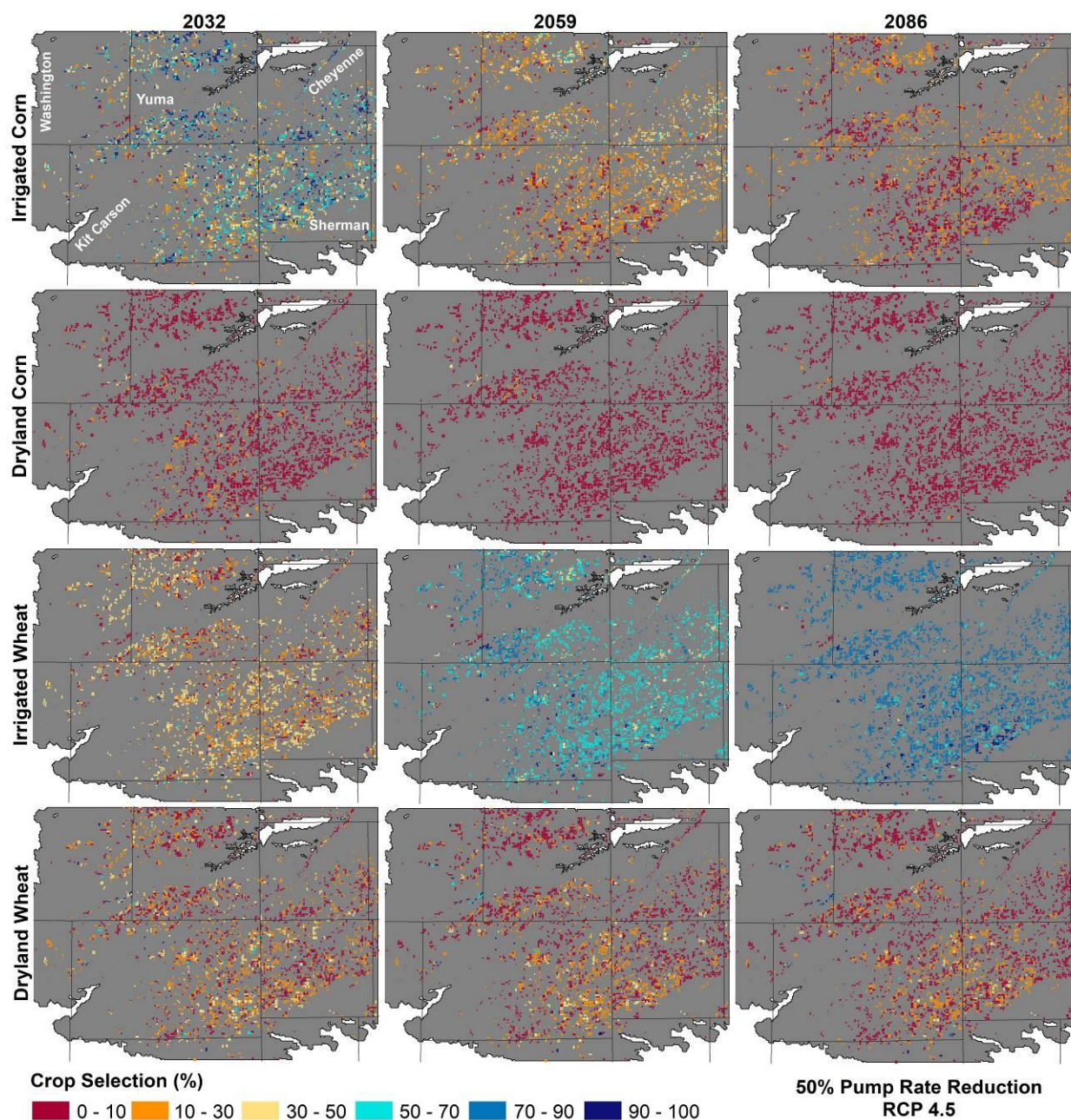


Figure C14. Percentages of selected crops on farms across the study area for the years 2032, 2059, and 2086. The displayed values are ensemble means derived from the ABM-MODFLOW simulations under an ensemble of climate projections for RCP4.5 and the 50% authorized pump rate reduction policy. These three years are the median years of short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).

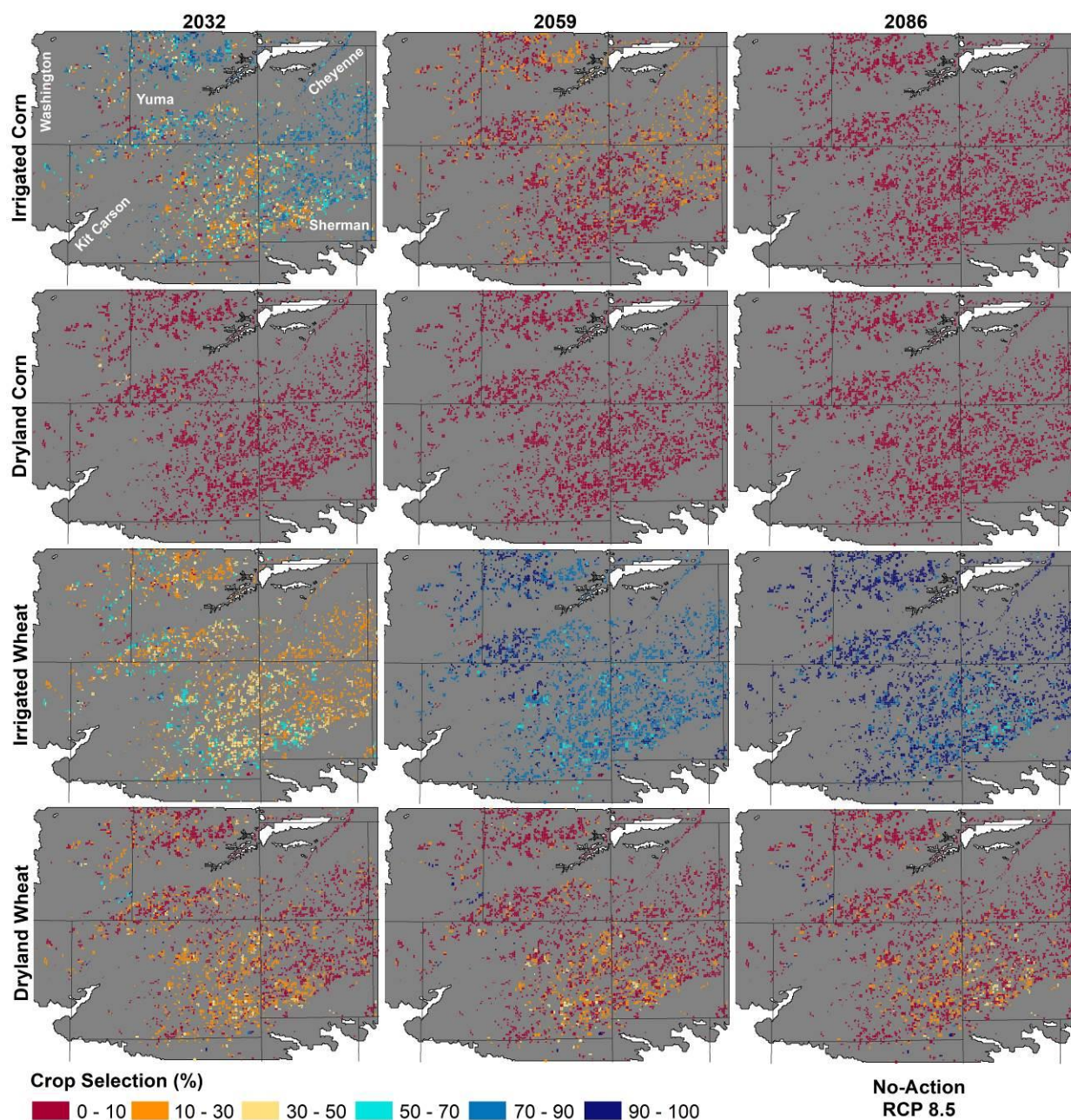


Figure C15. Percentages of selected crops on farms across the study area for the years 2032, 2059, and 2086. The displayed values are ensemble means derived from the ABM-MODFLOW simulations under an ensemble of climate projections for RCP8.5 and the no-action management scenario. These three years are the median years of short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).

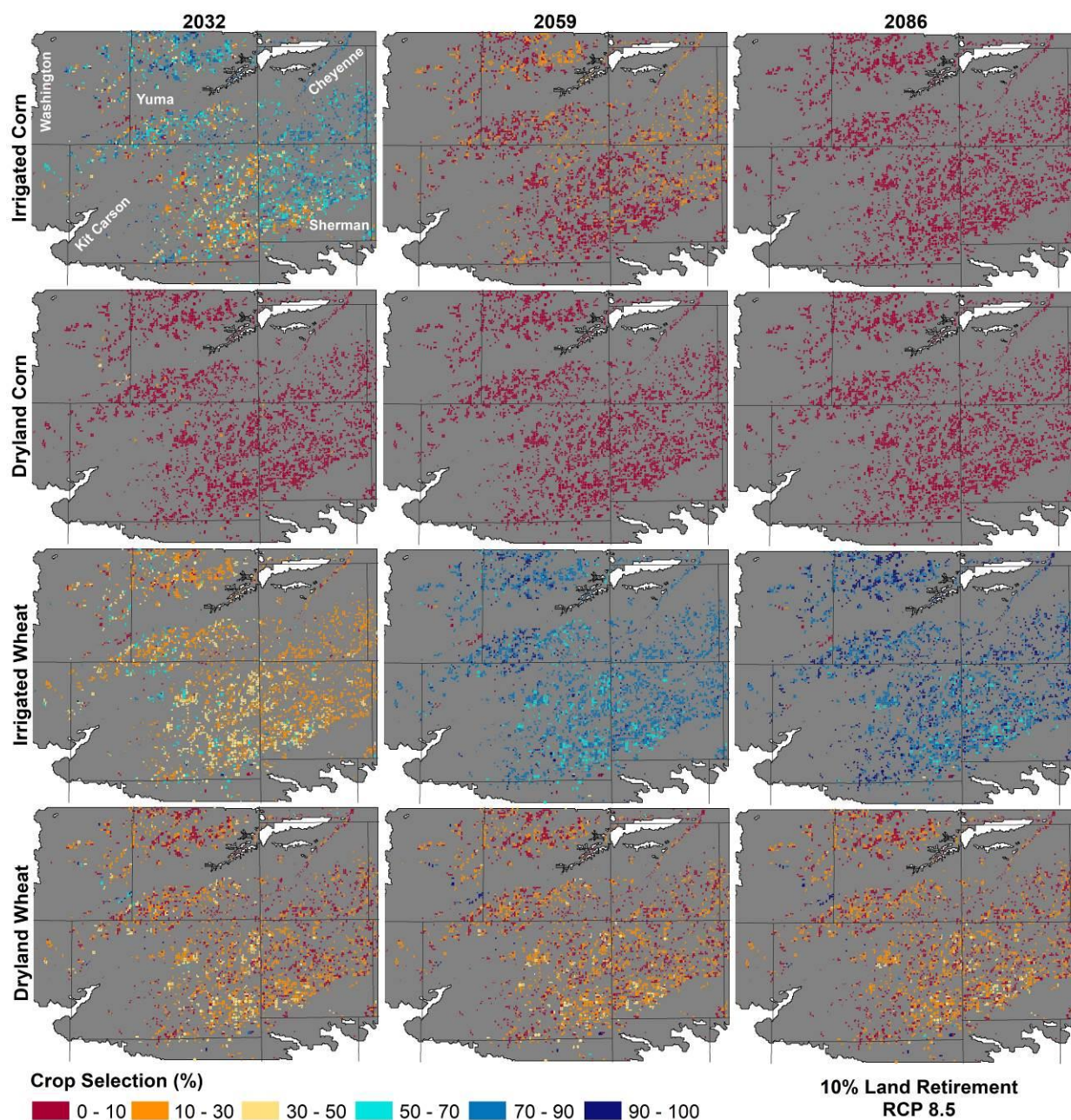


Figure C16. Percentages of selected crops on farms across the study area for the years 2032, 2059, and 2086. The displayed values are ensemble means derived from the ABM-MODFLOW simulations under an ensemble of climate projections for RCP8.5 and the 10% irrigated land retirement policy. These three years are the median years of short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).

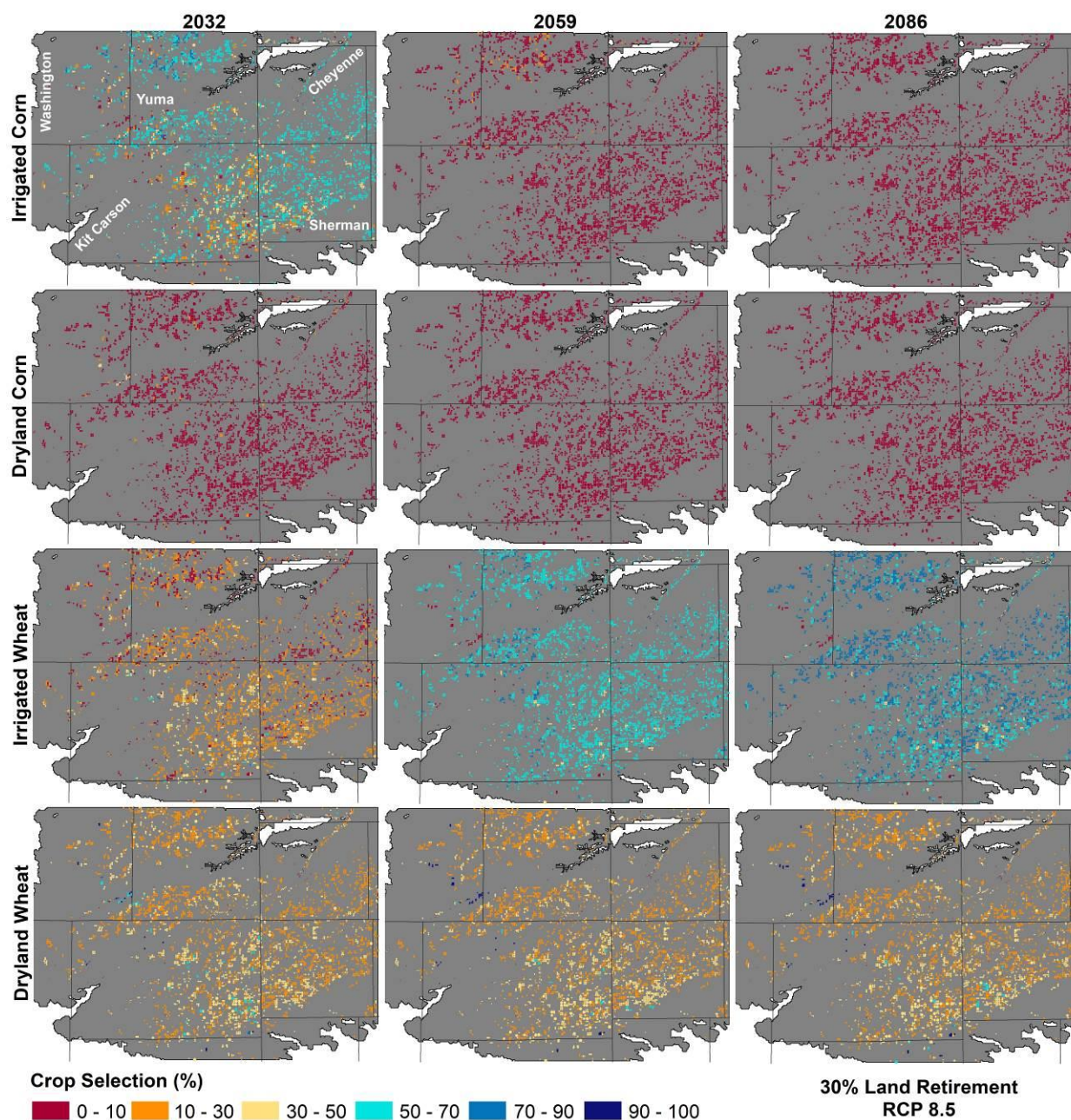


Figure C17. Percentages of selected crops on farms across the study area for the years 2032, 2059, and 2086. The displayed values are ensemble means derived from the ABM-MODFLOW simulations under an ensemble of climate projections for RCP8.5 and the 30% irrigated land retirement policy. These three years are the median years of short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).

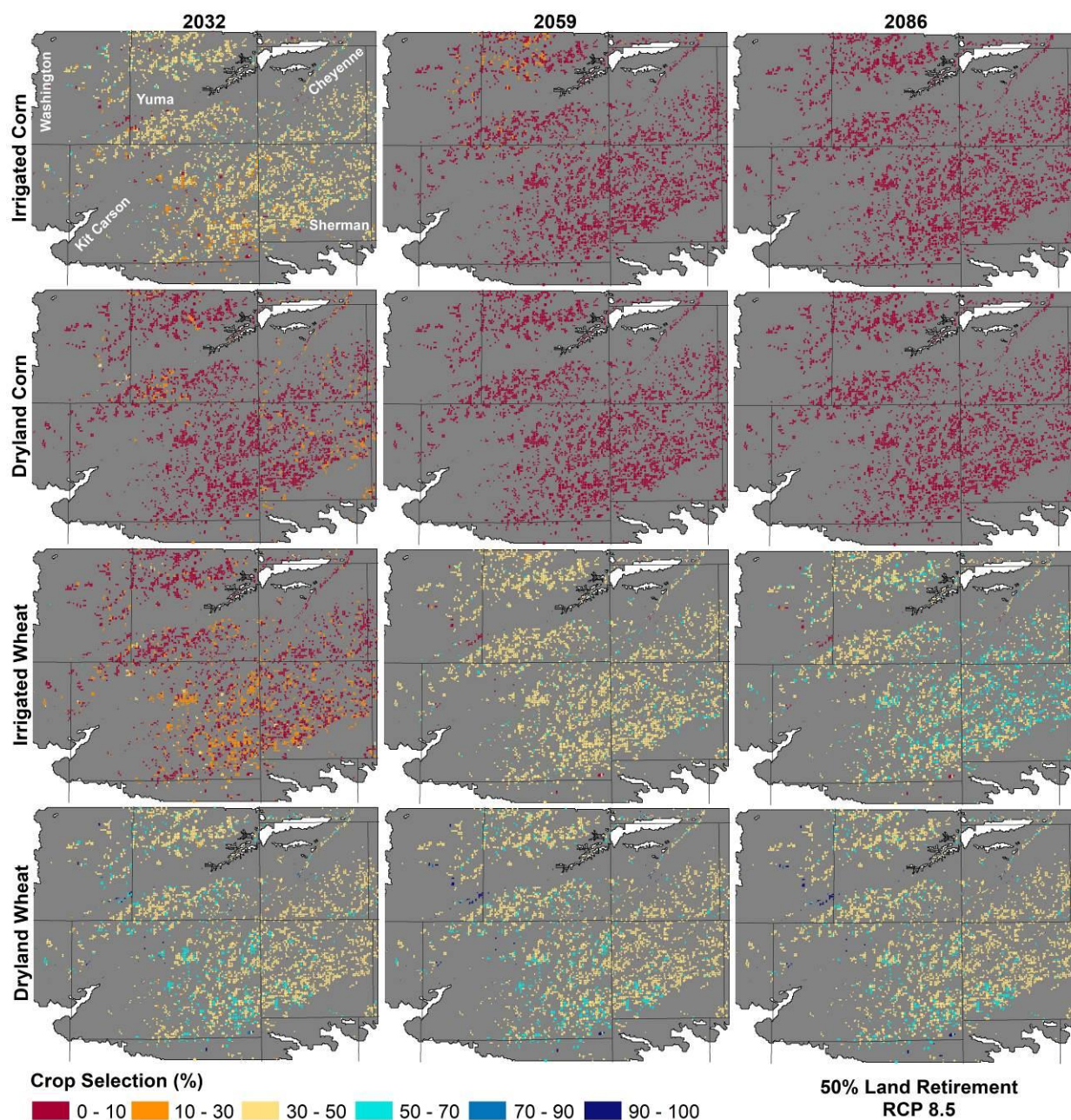


Figure C18. Percentages of selected crops on farms across the study area for the years 2032, 2059, and 2086. The displayed values are ensemble means derived from the ABM-MODFLOW simulations under an ensemble of climate projections for RCP8.5 and the 50% irrigated land retirement policy. These three years are the median years of short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).

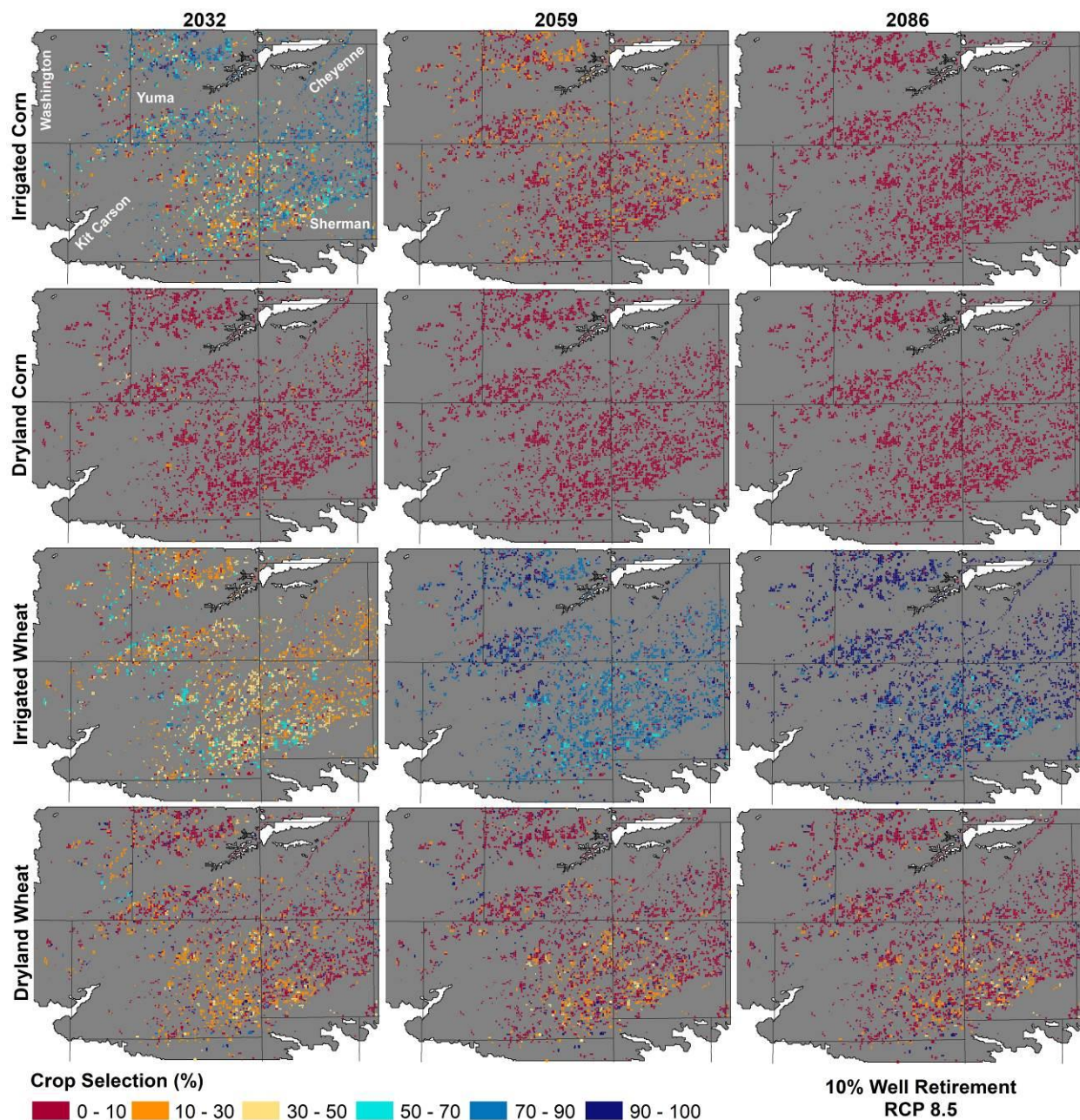


Figure C19. Percentages of selected crops on farms across the study area for the years 2032, 2059, and 2086. The displayed values are ensemble means derived from the ABM-MODFLOW simulations under an ensemble of climate projections for RCP8.5 and the 10% irrigation well retirement policy. These three years are the median years of short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).

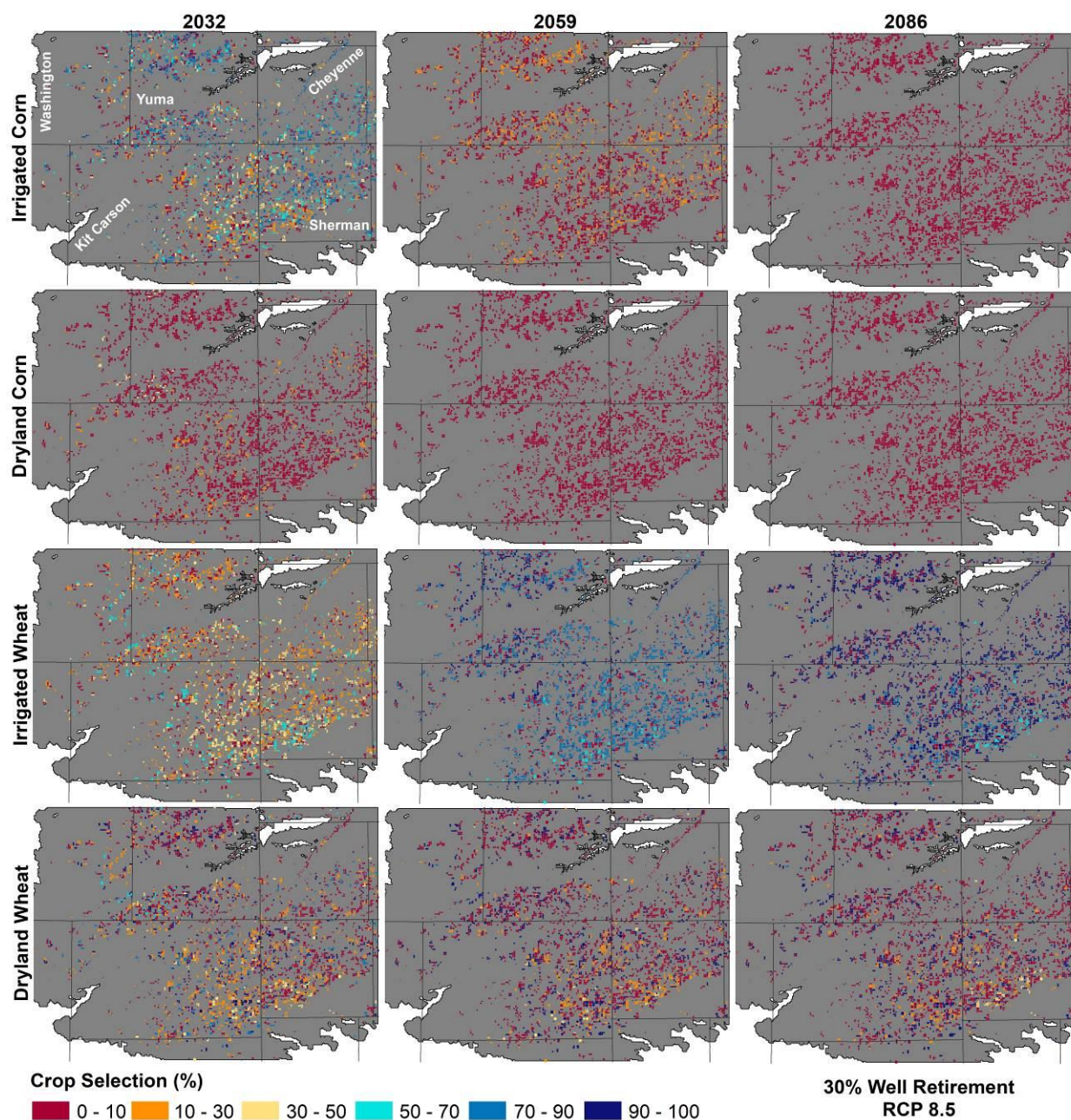


Figure C20. Percentages of selected crops on farms across the study area for the years 2032, 2059, and 2086. The displayed values are ensemble means derived from the ABM-MODFLOW simulations under an ensemble of climate projections for RCP8.5 and the 30% irrigation well retirement policy. These three years are the median years of short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).

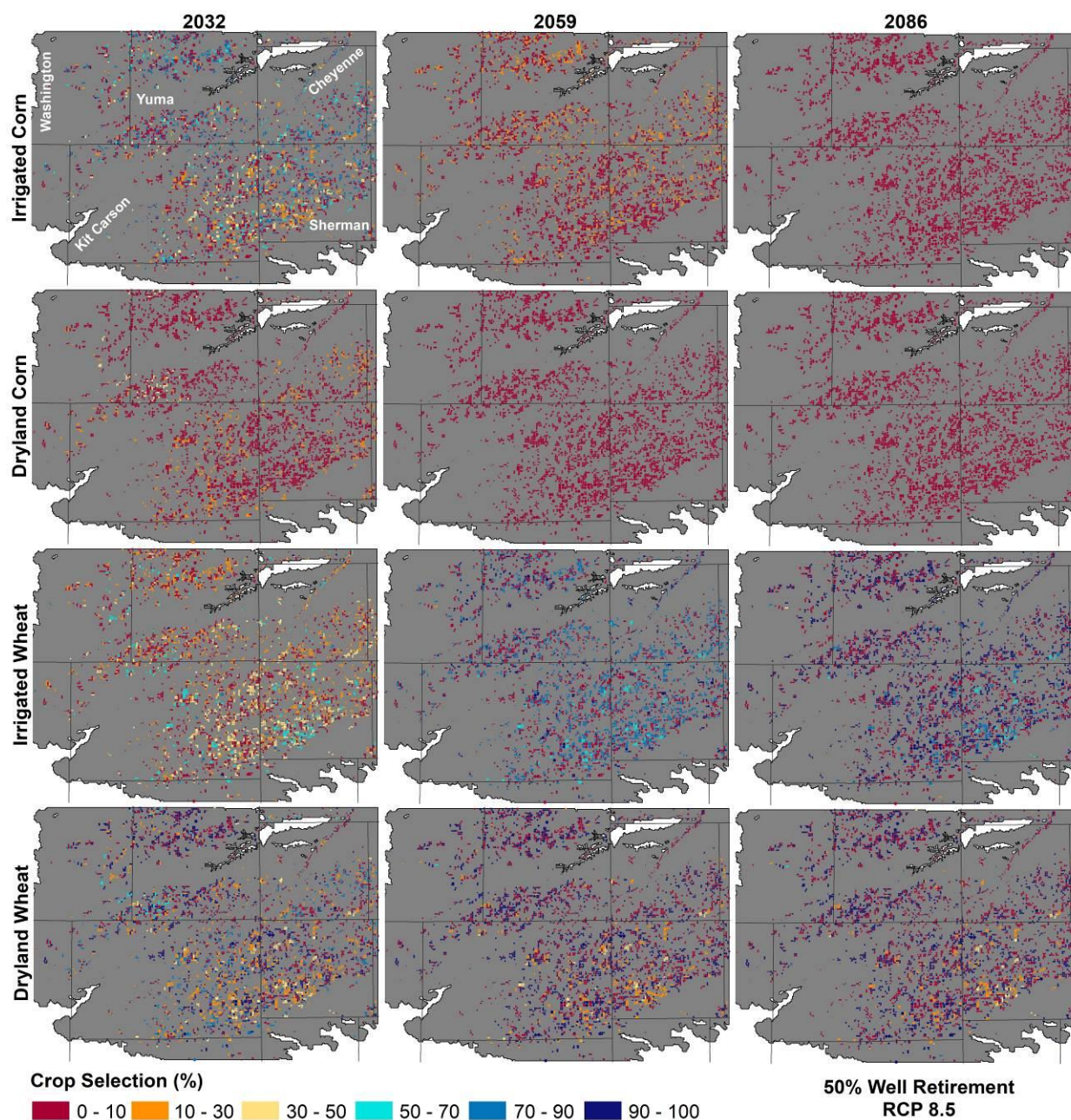


Figure C21. Percentages of selected crops on farms across the study area for the years 2032, 2059, and 2086. The displayed values are ensemble means derived from the ABM-MODFLOW simulations under an ensemble of climate projections for RCP8.5 and the 50% irrigation well retirement policy. These three years are the median years of short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).

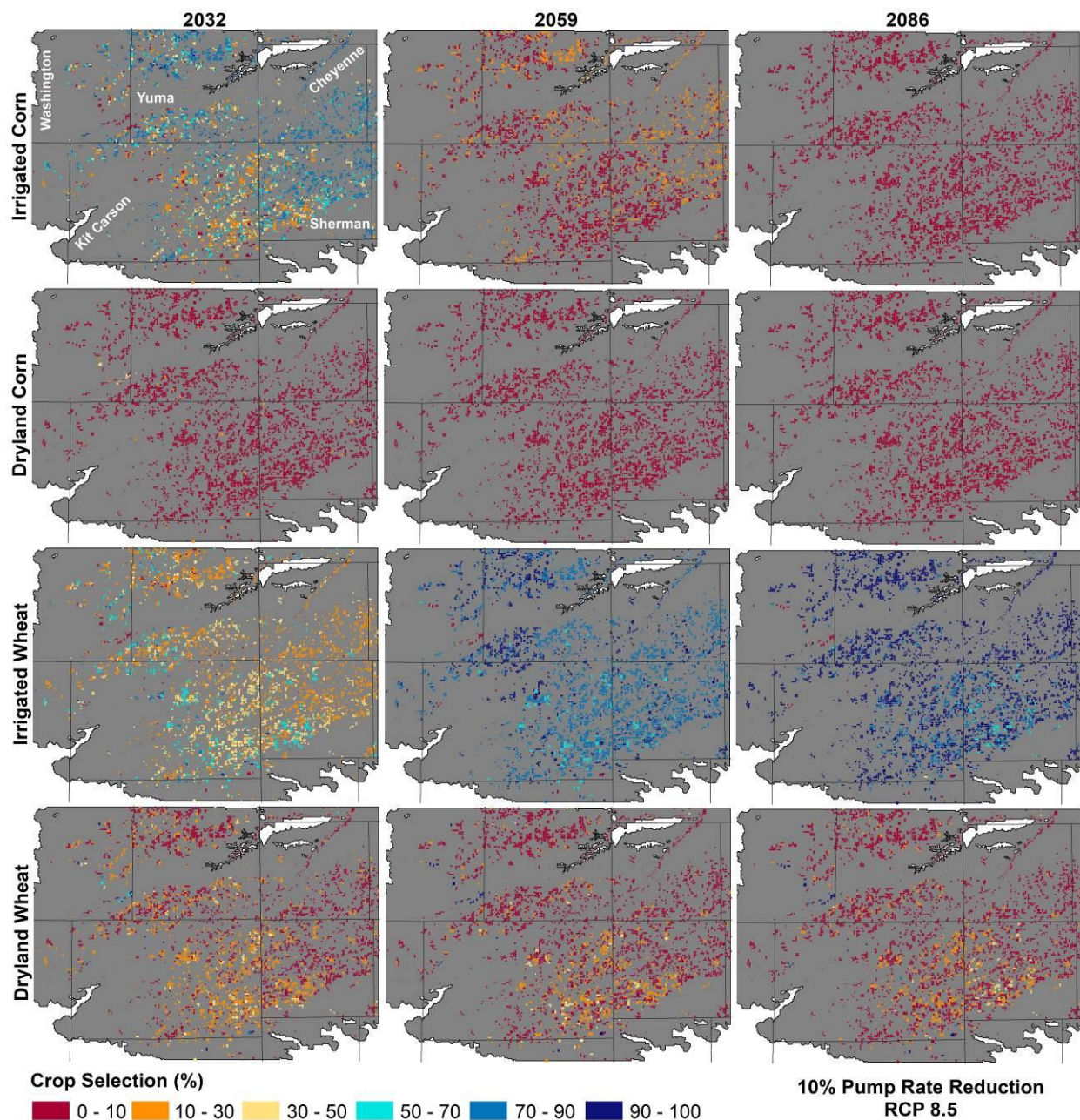


Figure C22. Percentages of selected crops on farms across the study area for the years 2032, 2059, and 2086. The displayed values are ensemble means derived from the ABM-MODFLOW simulations under an ensemble of climate projections for RCP8.5 and the 10% authorized pump rate reduction policy. These three years are the median years of short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).

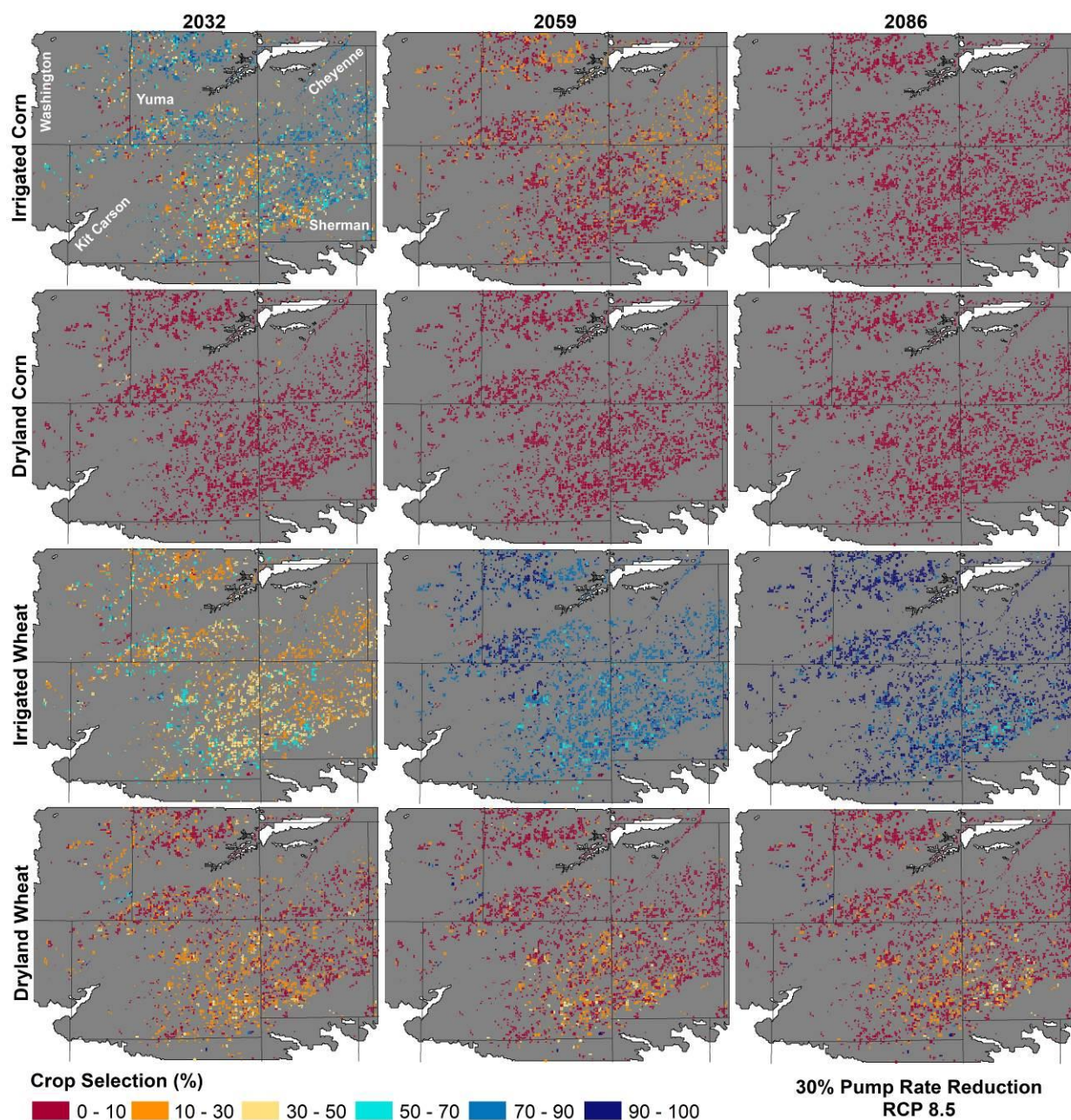


Figure C23. Percentages of selected crops on farms across the study area for the years 2032, 2059, and 2086. The displayed values are ensemble means derived from the ABM-MODFLOW simulations under an ensemble of climate projections for RCP8.5 and the 30% authorized pump rate reduction policy. These three years are the median years of short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).

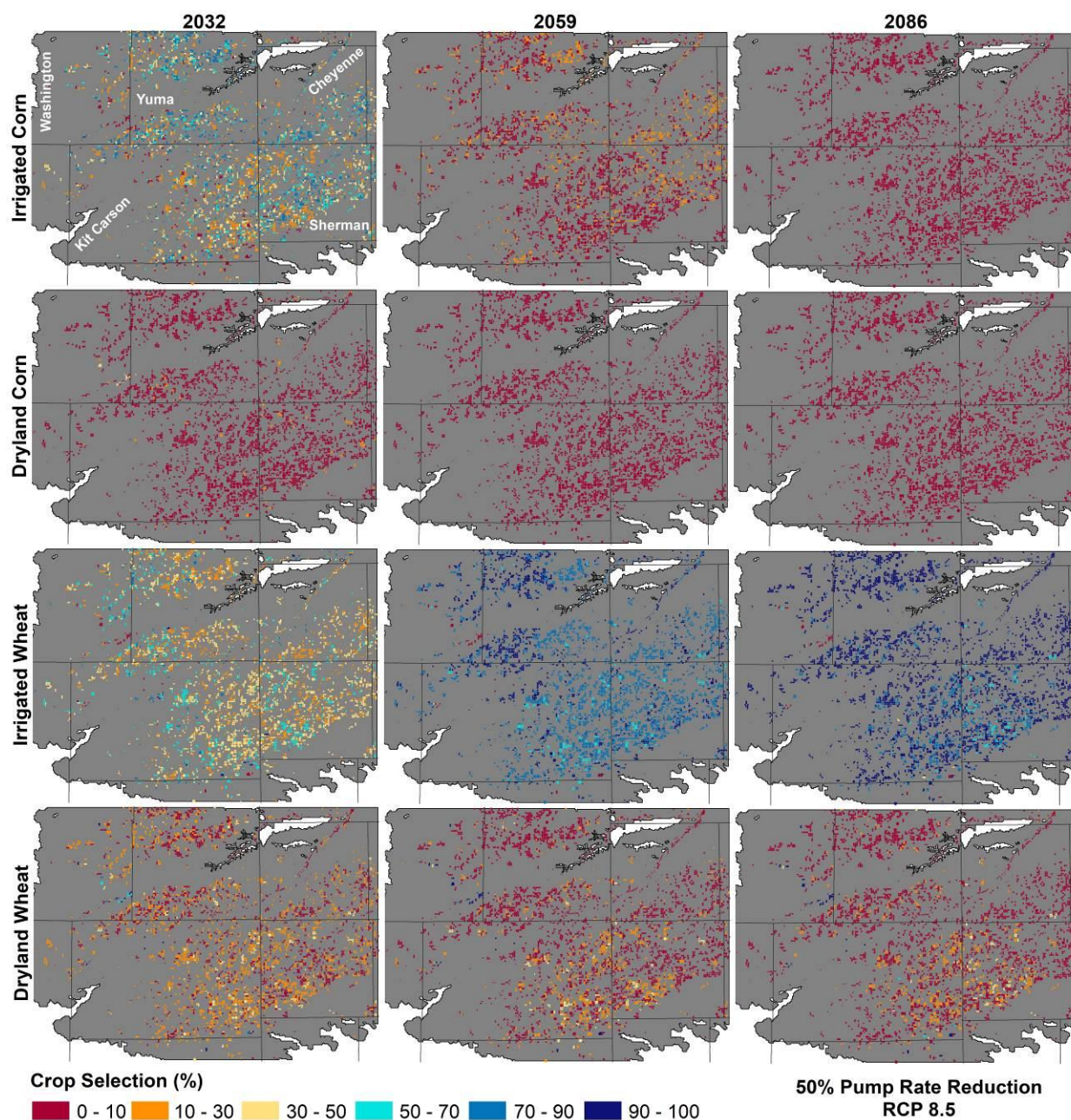


Figure C24. Percentages of selected crops on farms across the study area for the years 2032, 2059, and 2086. The displayed values are ensemble means derived from the ABM-MODFLOW simulations under an ensemble of climate projections for RCP8.5 and the 50% authorized pump rate reduction policy. These three years are the median years of short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).

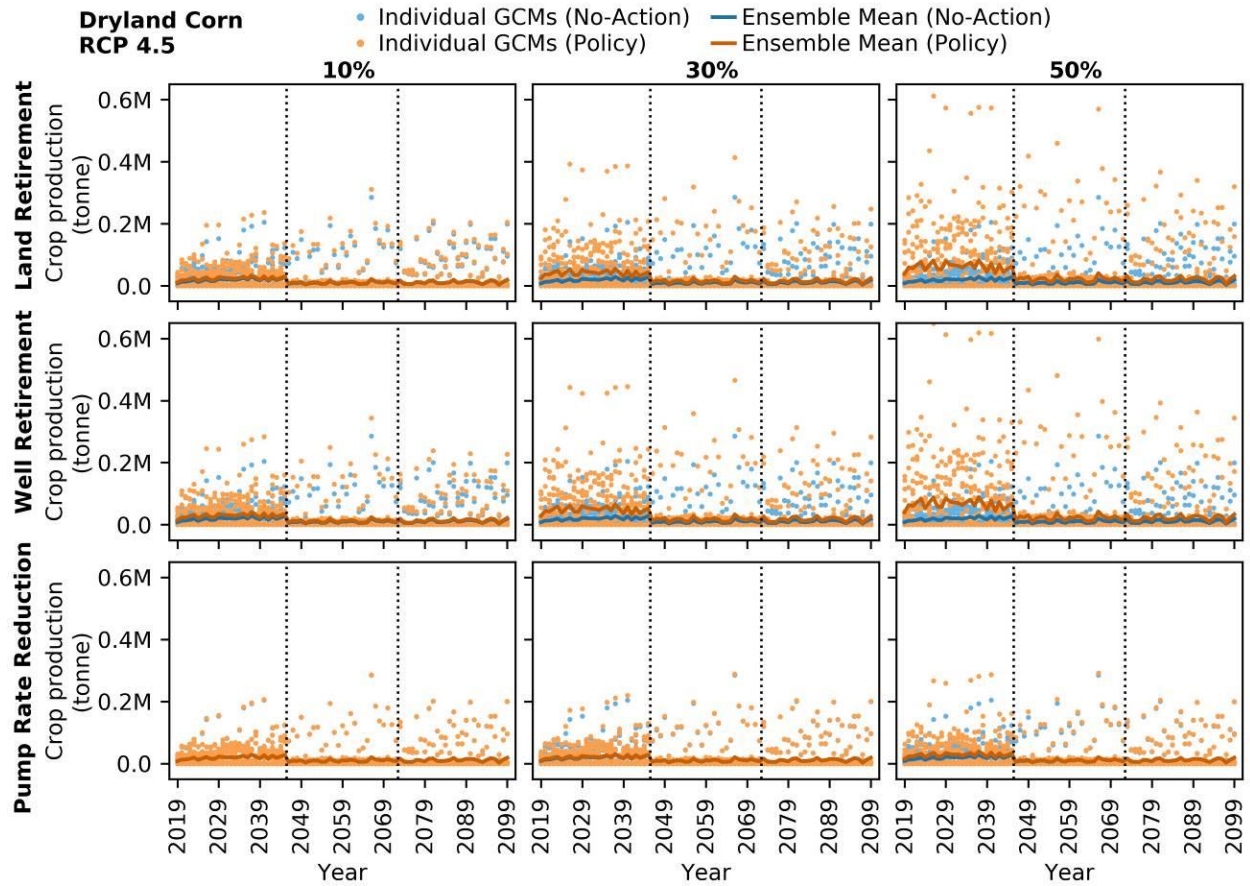


Figure C25. Dryland corn production as simulated by the ABM-MODFLOW, based on projections from an ensemble of global climate models (GCMs) for RCP4.5 under various management scenarios. Dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099). The abrupt changes between these periods arise from updating the distribution of climate outcomes in the economic model at the beginning of each period.

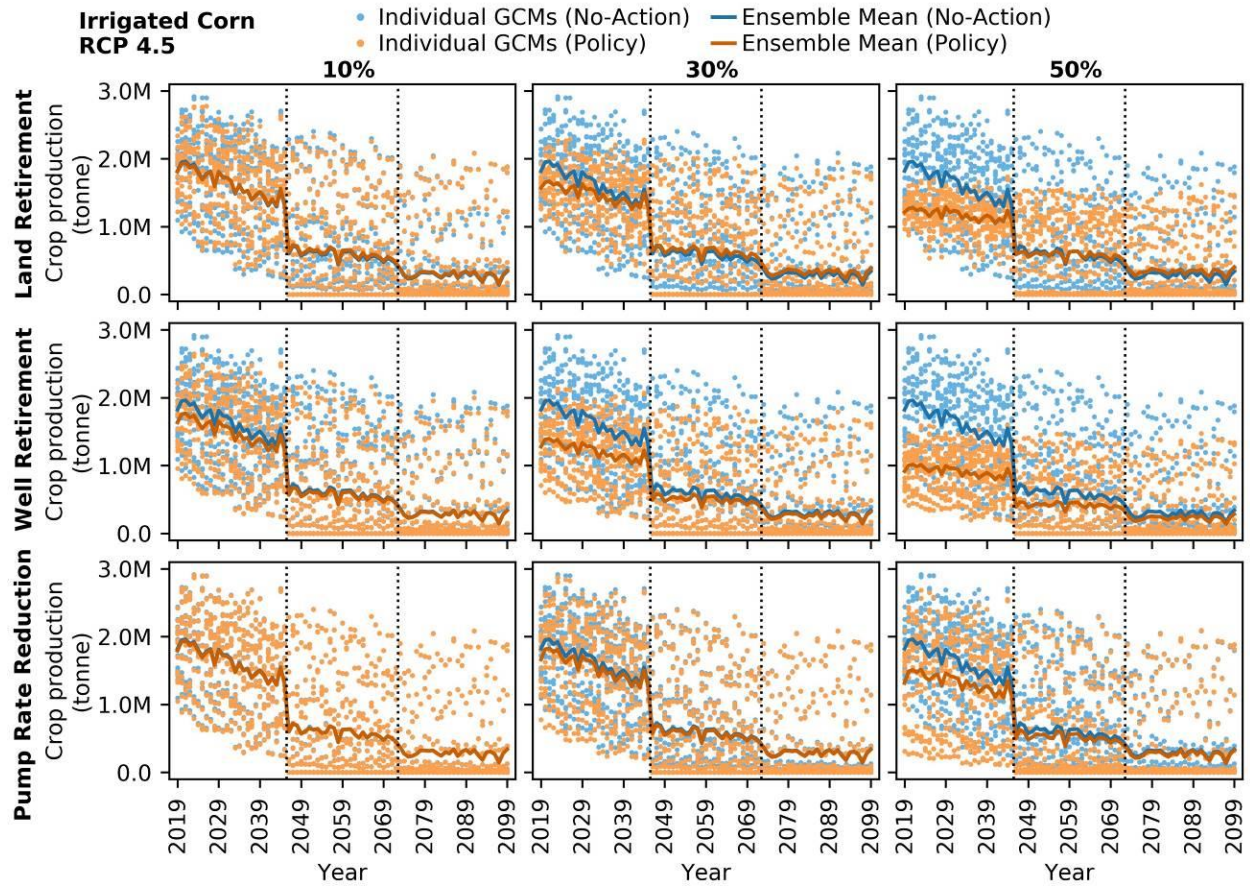


Figure C26. Irrigated corn production as simulated by the ABM-MODFLOW, based on projections from an ensemble of global climate models (GCMs) for RCP4.5 under various management scenarios. Dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099). The abrupt changes between these periods arise from updating the distribution of climate outcomes in the economic model at the beginning of each period.

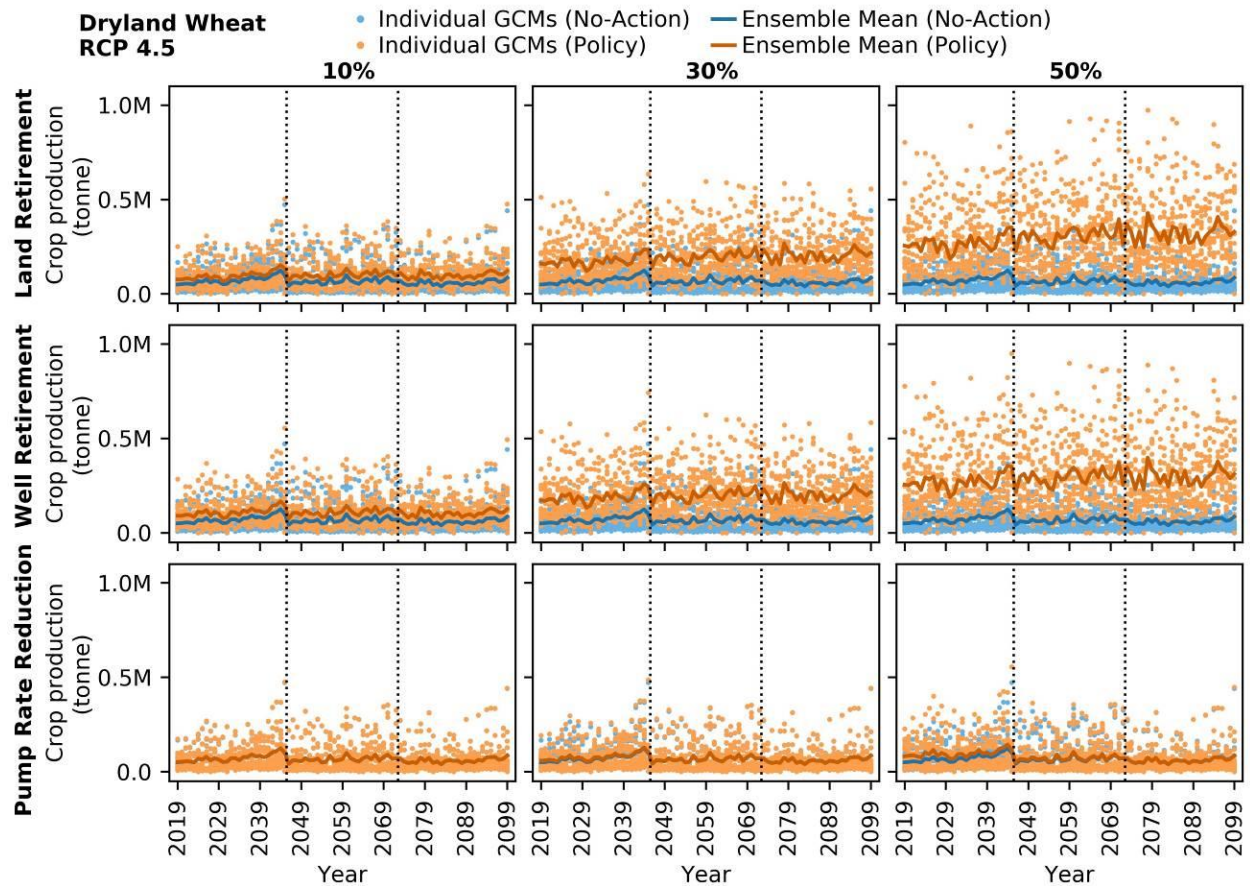


Figure C27. Dryland winter wheat production as simulated by the ABM-MODFLOW, based on projections from an ensemble of global climate models (GCMs) for RCP4.5 under various management scenarios. Dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099). The abrupt changes between these periods arise from updating the distribution of climate outcomes in the economic model at the beginning of each period.

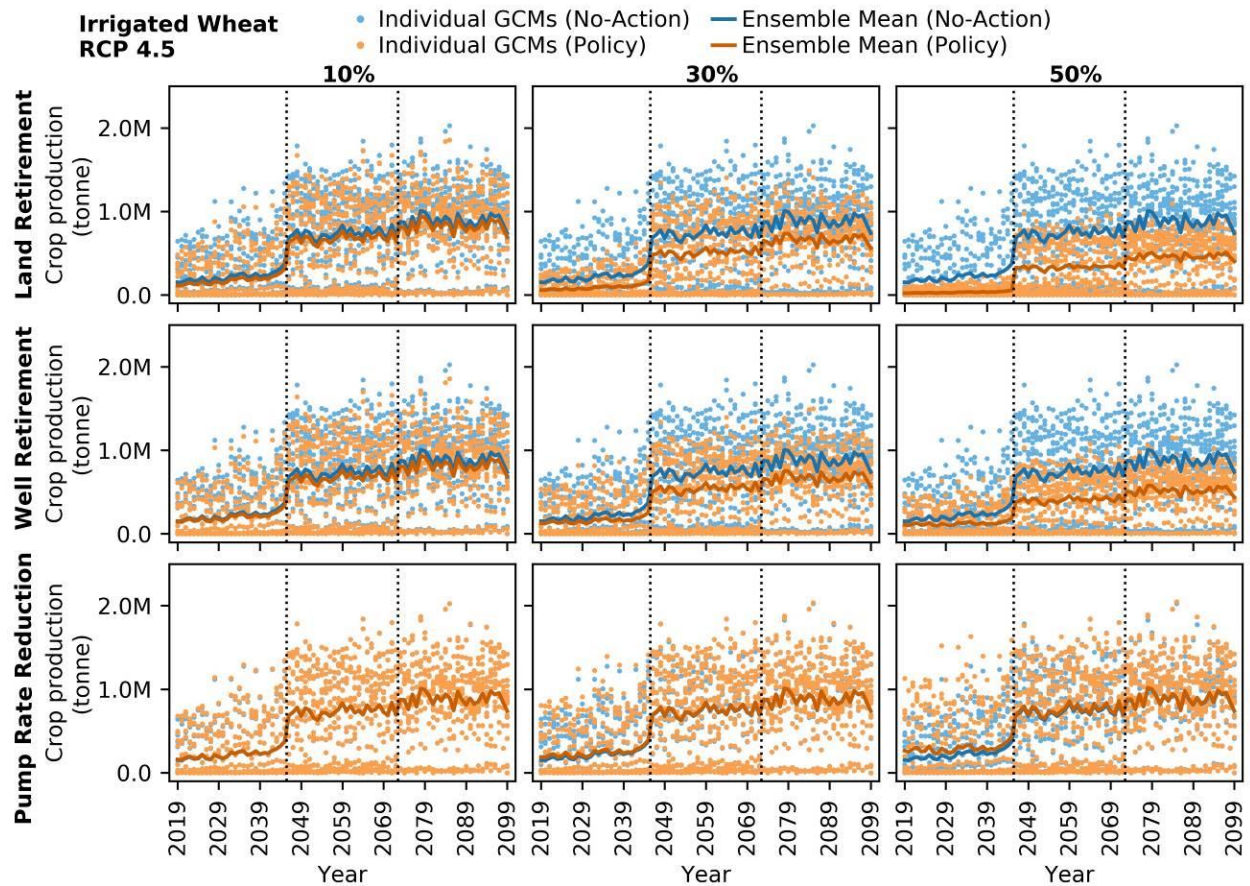


Figure C28. Irrigated winter wheat production as simulated by the ABM-MODFLOW, based on projections from an ensemble of global climate models (GCMs) for RCP4.5 under various management scenarios. Dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099). The abrupt changes between these periods arise from updating the distribution of climate outcomes in the economic model at the beginning of each period.

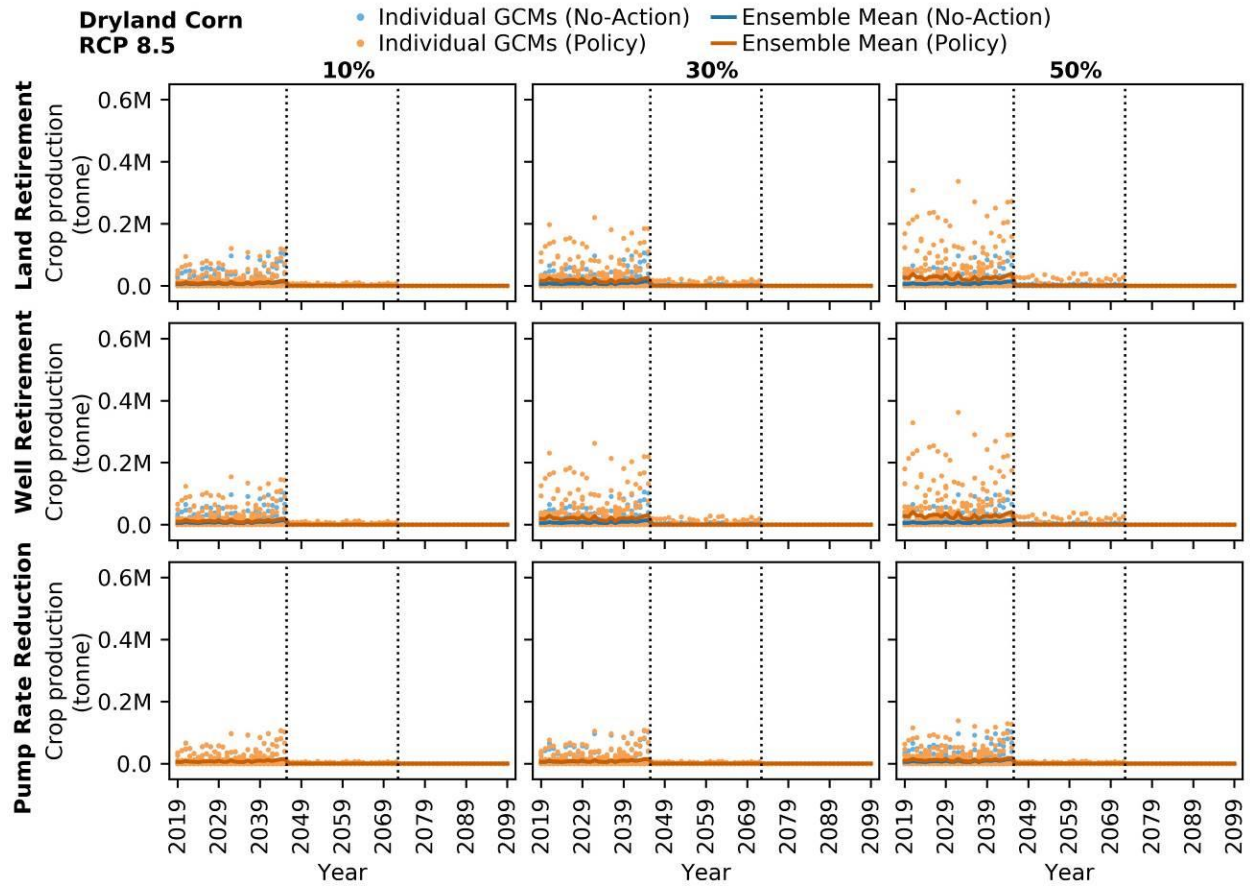


Figure C29. Dryland corn production as simulated by the ABM-MODFLOW, based on projections from an ensemble of global climate models (GCMs) for RCP8.5 under various management scenarios. Dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099). The abrupt changes between these periods arise from updating the distribution of climate outcomes in the economic model at the beginning of each period.

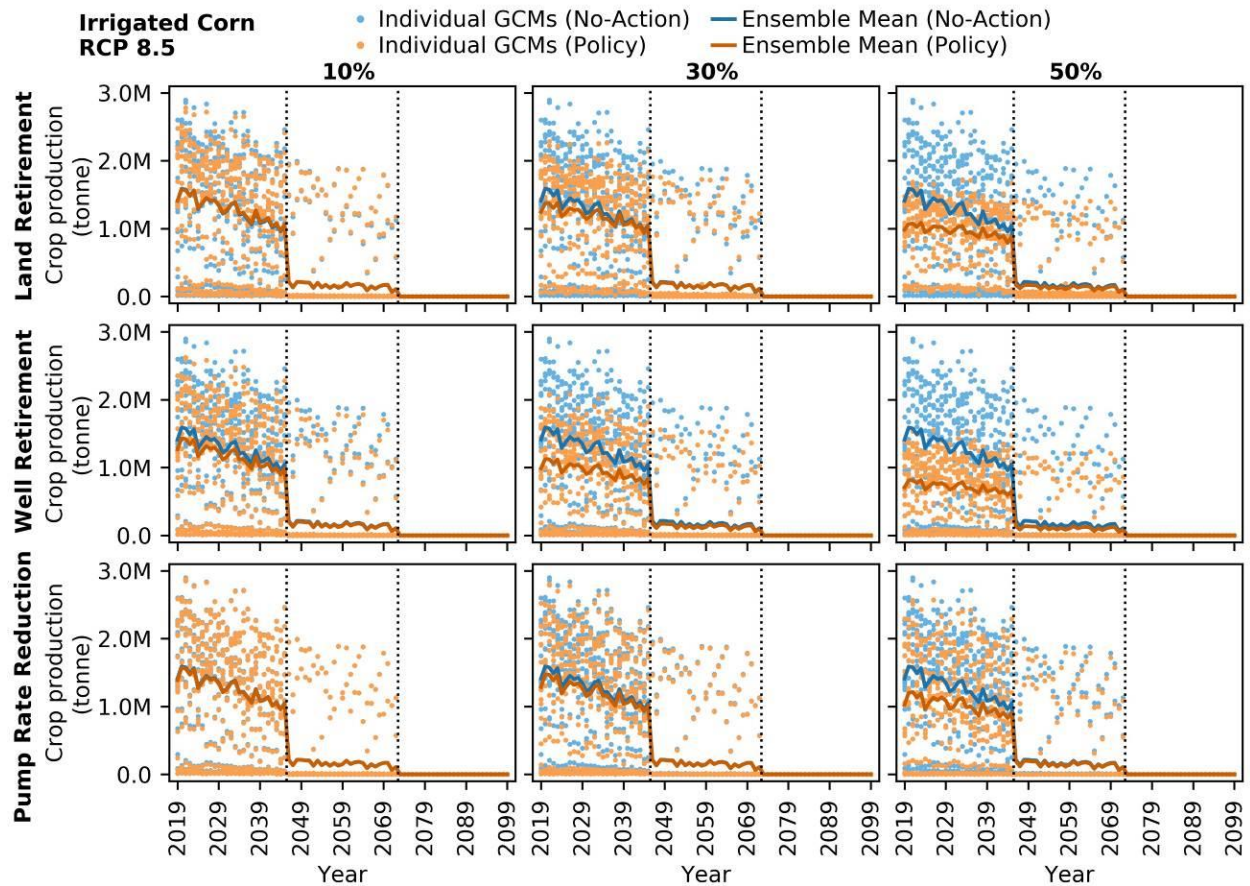


Figure C30. Irrigated corn production as simulated by the ABM-MODFLOW, based on projections from an ensemble of global climate models (GCMs) for RCP8.5 under various management scenarios. Dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099). The abrupt changes between these periods arise from updating the distribution of climate outcomes in the economic model at the beginning of each period.

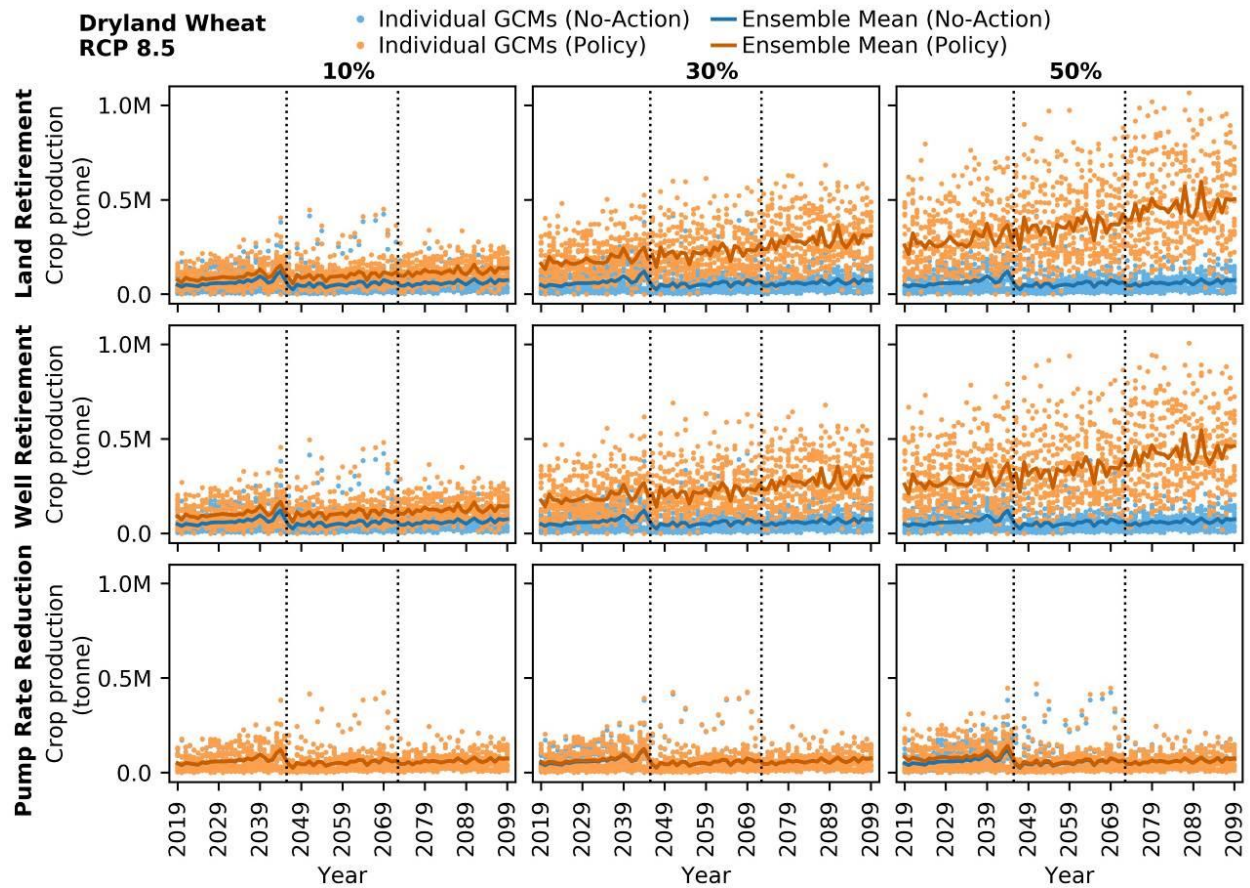


Figure C31. Dryland winter wheat production as simulated by the ABM-MODFLOW, based on projections from an ensemble of global climate models (GCMs) for RCP8.5 under various management scenarios. Dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099). The abrupt changes between these periods arise from updating the distribution of climate outcomes in the economic model at the beginning of each period.

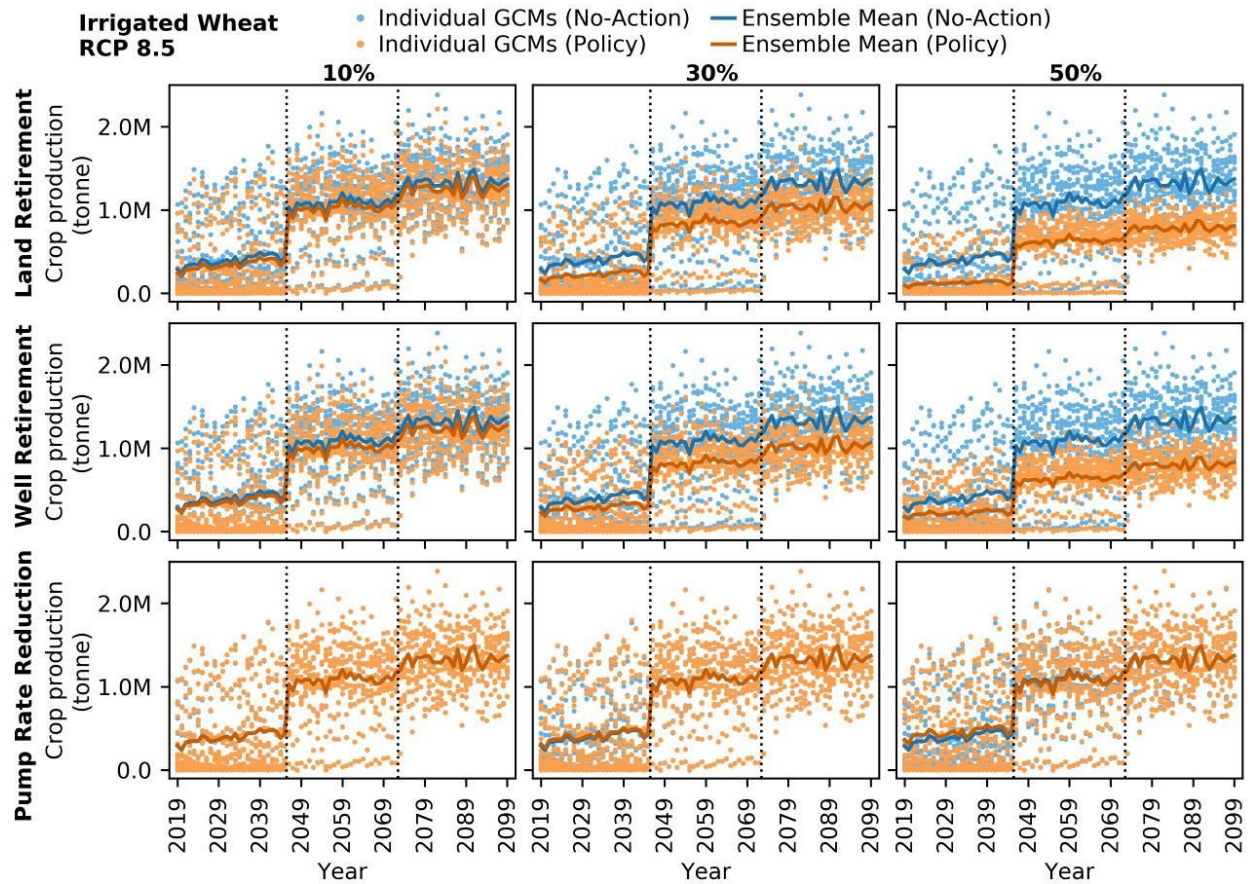


Figure C32. Irrigated winter wheat production as simulated by the ABM-MODFLOW, based on projections from an ensemble of global climate models (GCMs) for RCP8.5 under various management scenarios. Dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099). The abrupt changes between these periods arise from updating the distribution of climate outcomes in the economic model at the beginning of each period.

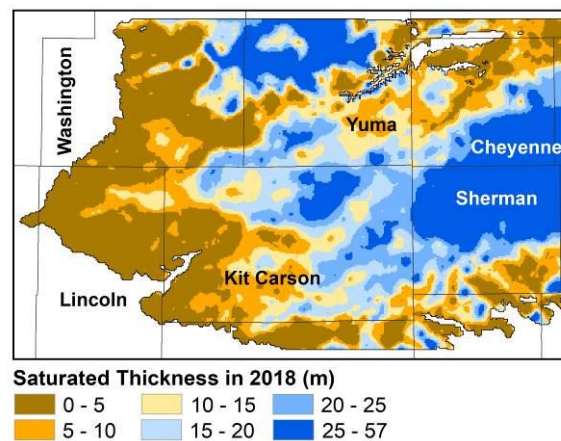


Figure C33. The aquifer's saturated thickness (the vertical distance between the water table and bedrock) in 2018.

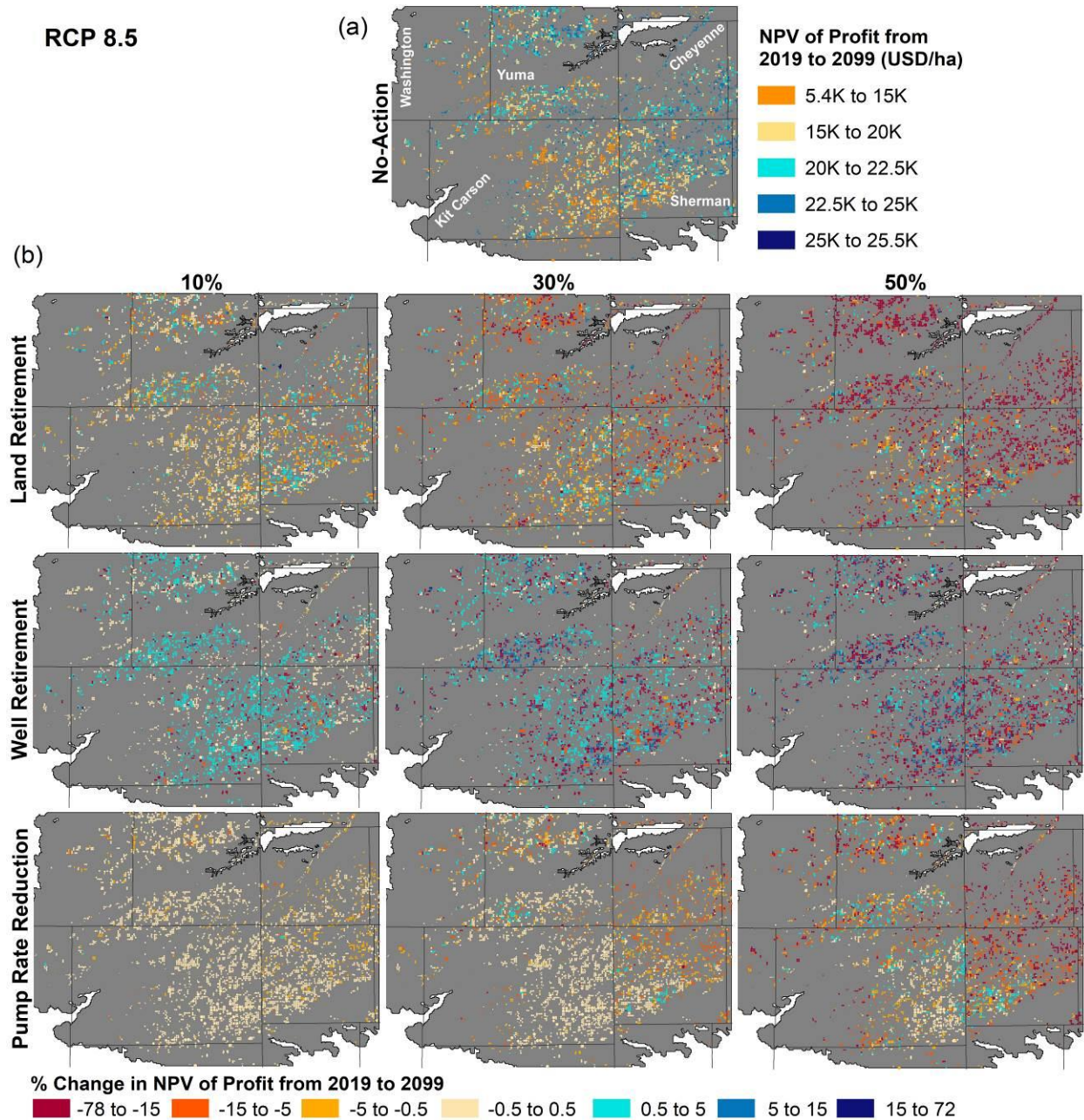


Figure C34. Influence of groundwater management policies on farmers' profitability across the region under RCP8.5. (a) Net present value (NPV) of profit per unit land area for individual farmers under the no-action scenario, with NPV calculated as the ensemble mean of simulation outcomes under climate projections from multiple global climate models (GCMs). (b) Percent change in NPV of profit, relative to the no-action scenario, under different groundwater management policies.

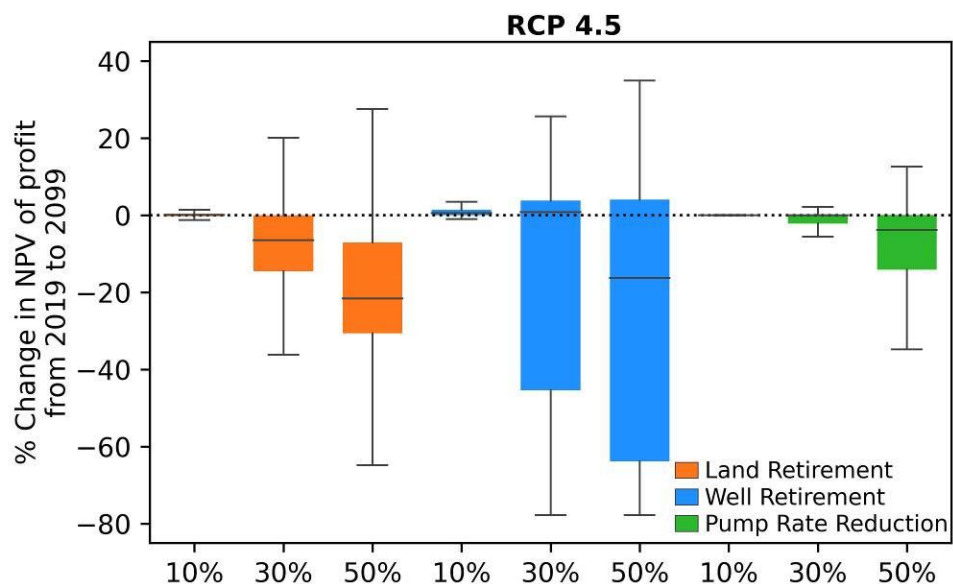


Figure C35. Distribution of the percent change in farmers' net present value (*NPV*) of profit, relative to the no-action scenario, under different groundwater management policies. *NPV* is calculated as the ensemble mean of simulation outcomes under climate projections from multiple global climate models (GCMs) for RCP4.5.

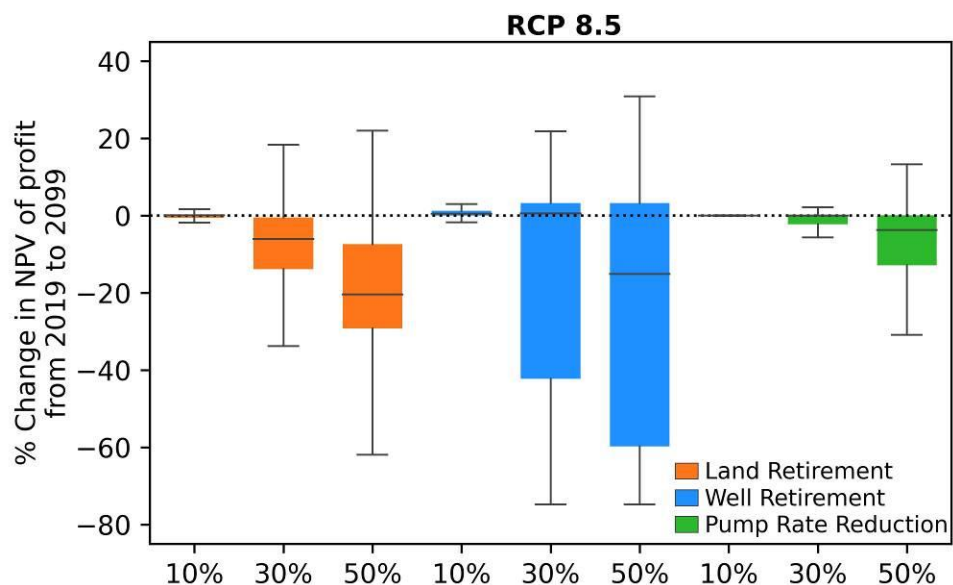


Figure C36. Distribution of the percent change in farmers' net present value (*NPV*) of profit, relative to the no-action scenario, under different groundwater management policies. *NPV* is calculated as the ensemble mean of simulation outcomes under climate projections from multiple global climate models (GCMs) for RCP8.5.

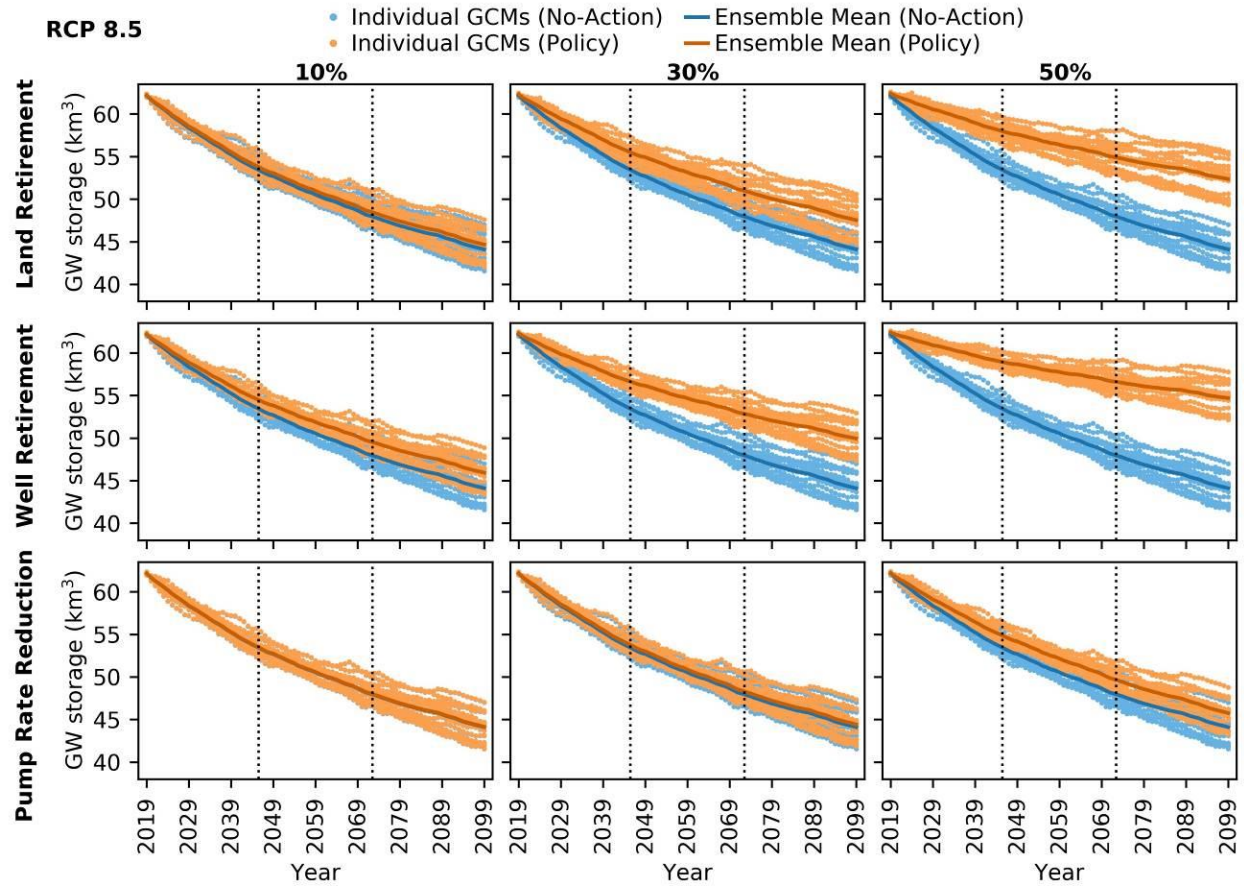


Figure C37. Total groundwater storage in the study area as simulated by the ABM-MODFLOW, based on projections from an ensemble of global climate models (GCMs) for RCP8.5 under various management scenarios. Dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).

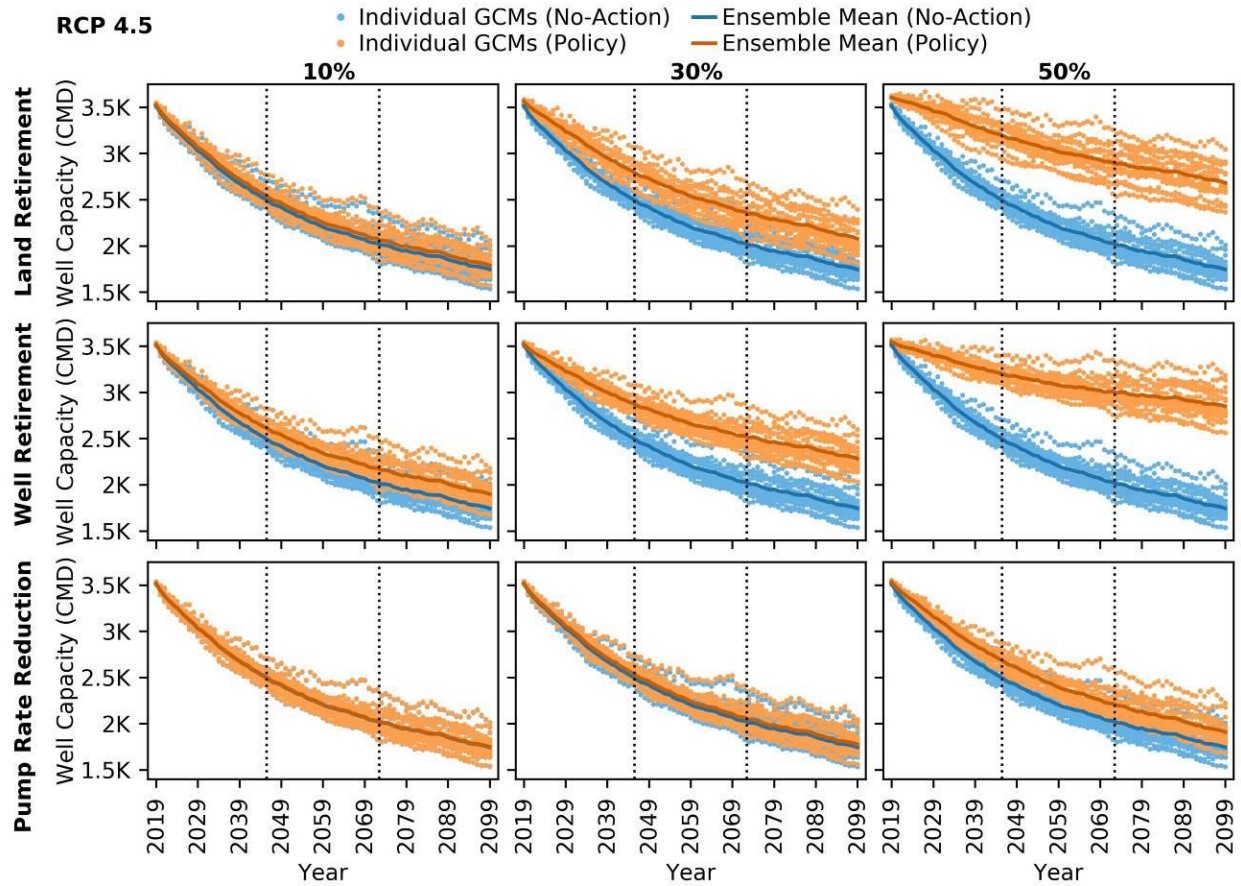


Figure C38. Average capacity of active irrigation wells, those not retired or depleted, in the study area, as simulated by the ABM-MODFLOW based on projections from an ensemble of global climate models (GCMs) for RCP4.5 under various management scenarios. Dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099). CMD denotes cubic meters per day.

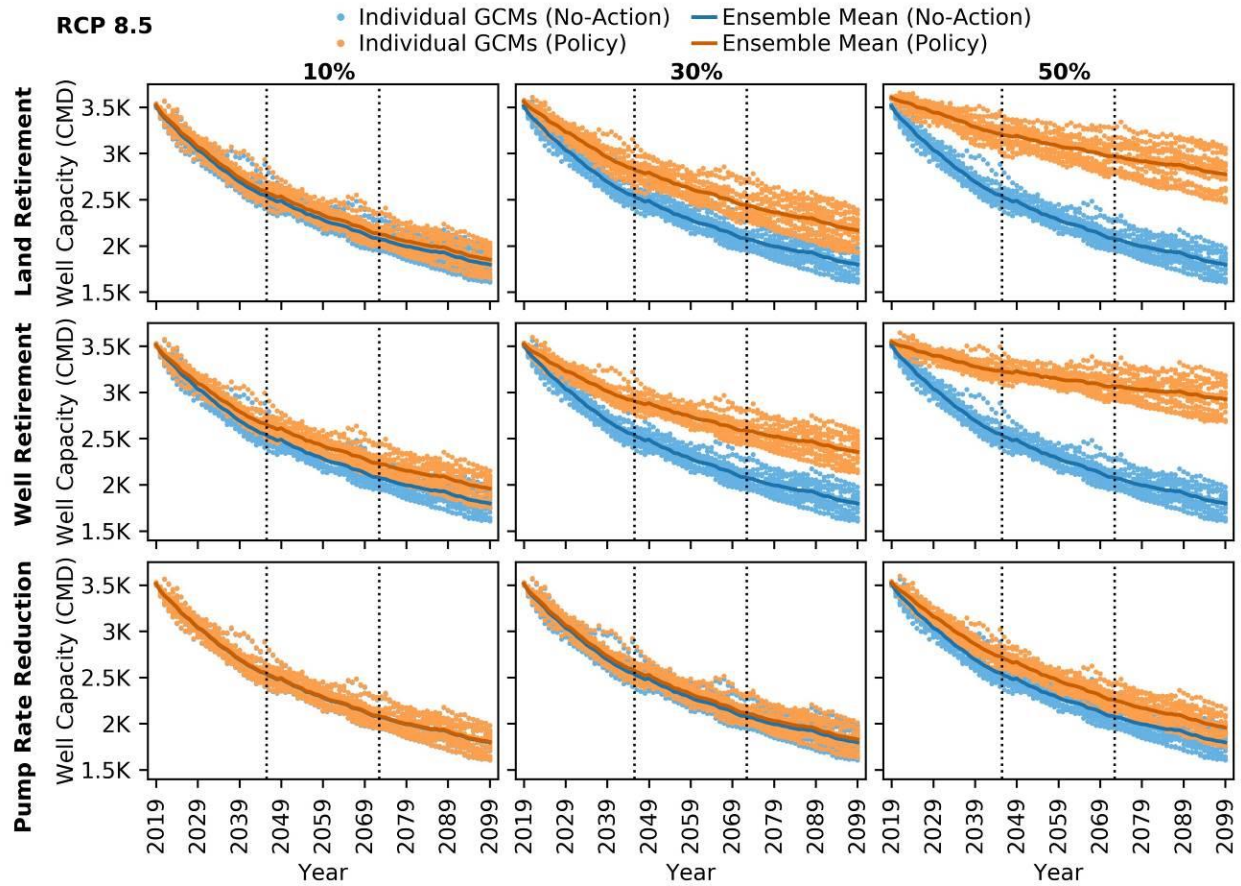


Figure C39. Average capacity of active irrigation wells, those not retired or depleted, in the study area, as simulated by the ABM-MODFLOW based on projections from an ensemble of global climate models (GCMs) for RCP8.5 under various management scenarios. Dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099). CMD denotes cubic meters per day.

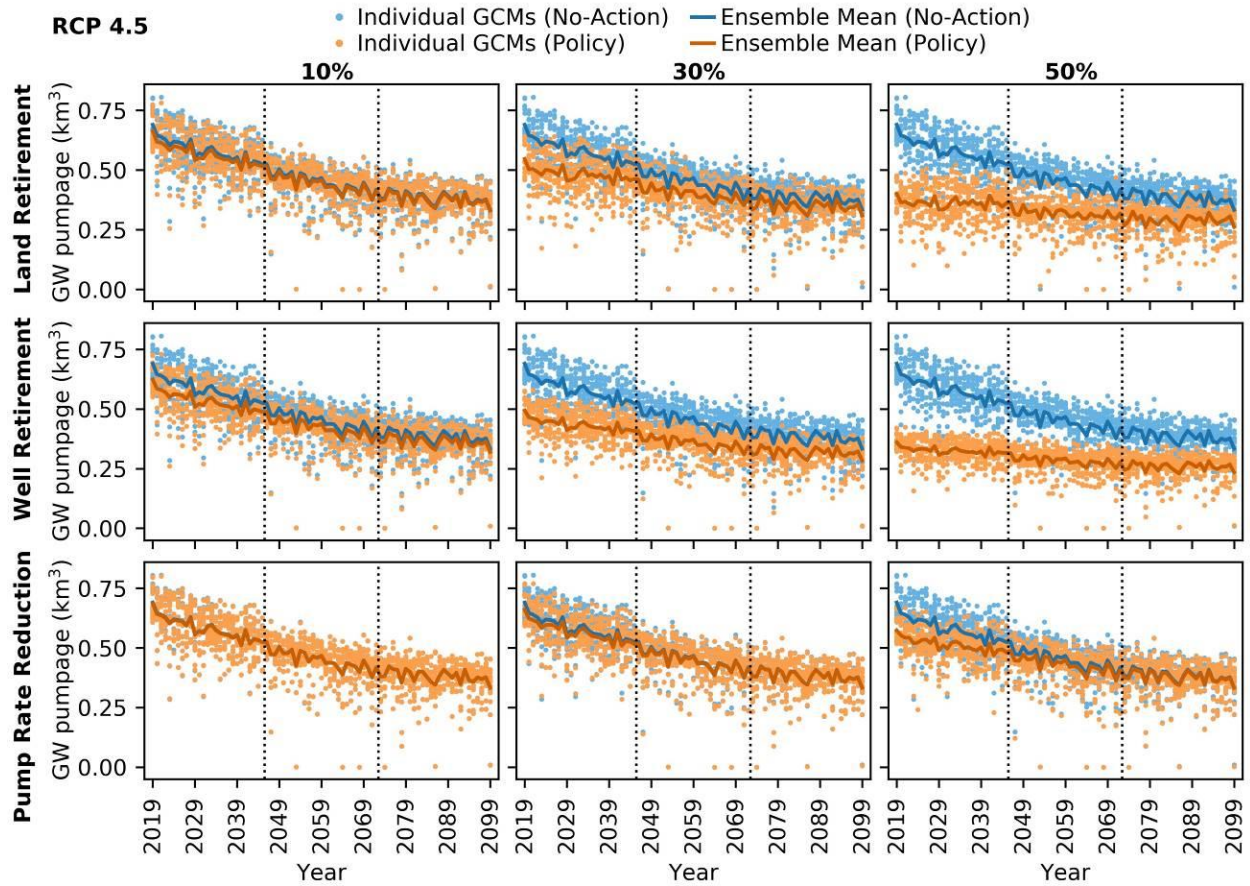


Figure C40. Total groundwater extraction for irrigation in the study area as simulated by the ABM-MODFLOW, based on projections from an ensemble of global climate models (GCMs) for RCP4.5 under various management scenarios. Dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).

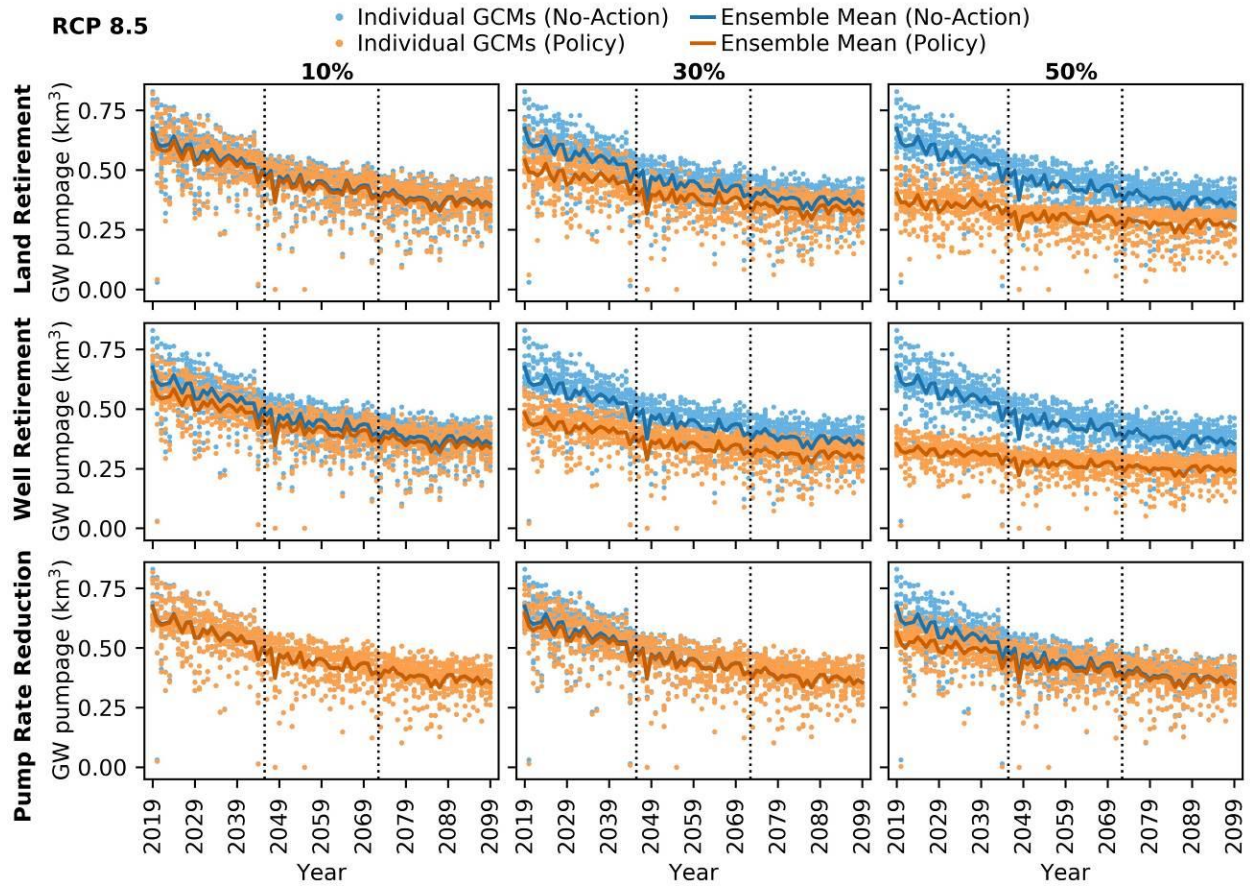


Figure C41. Total groundwater extraction for irrigation in the study area as simulated by the ABM-MODFLOW, based on projections from an ensemble of global climate models (GCMs) for RCP8.5 under various management scenarios. Dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).

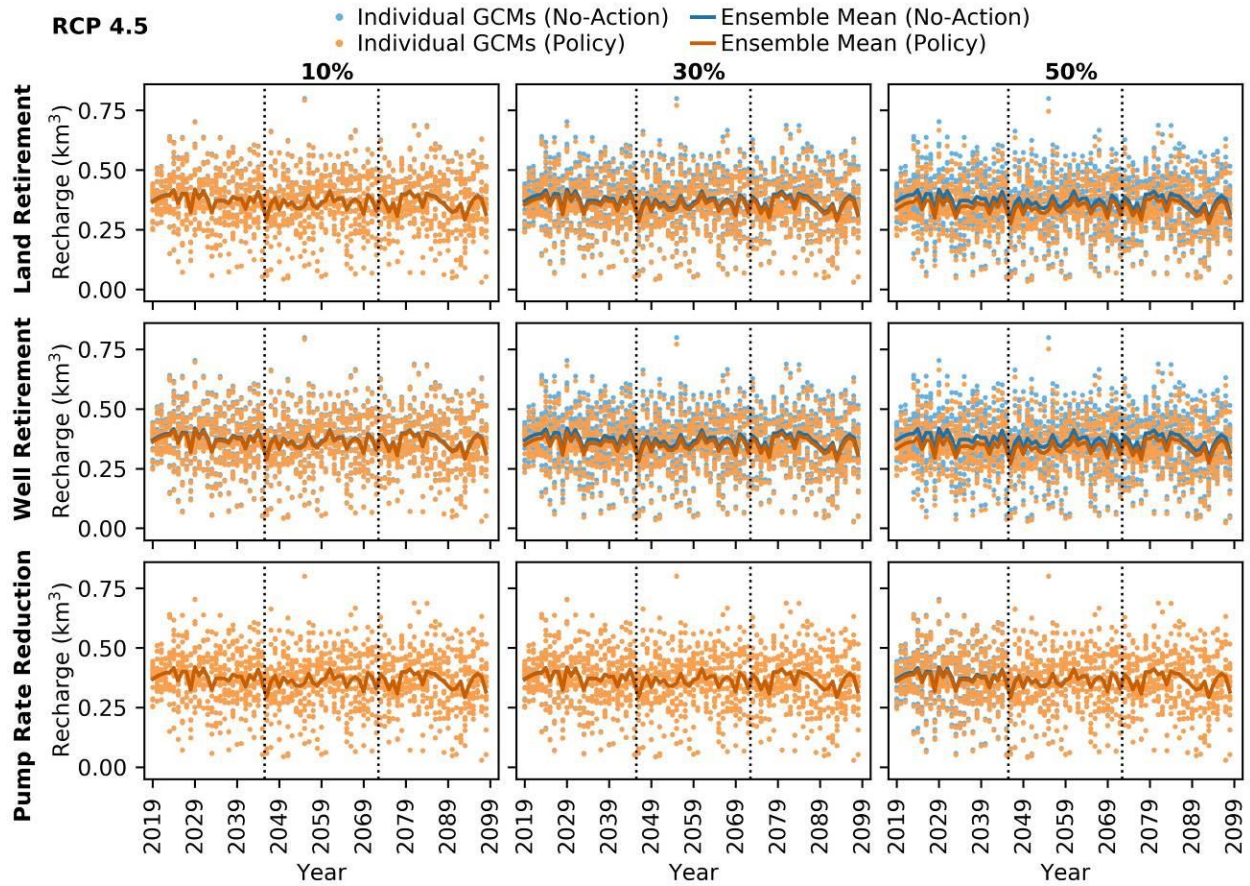


Figure C42. Total groundwater recharge in the study area as simulated by the ABM-MODFLOW, based on projections from an ensemble of global climate models (GCMs) for RCP4.5 under various management scenarios. Dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).

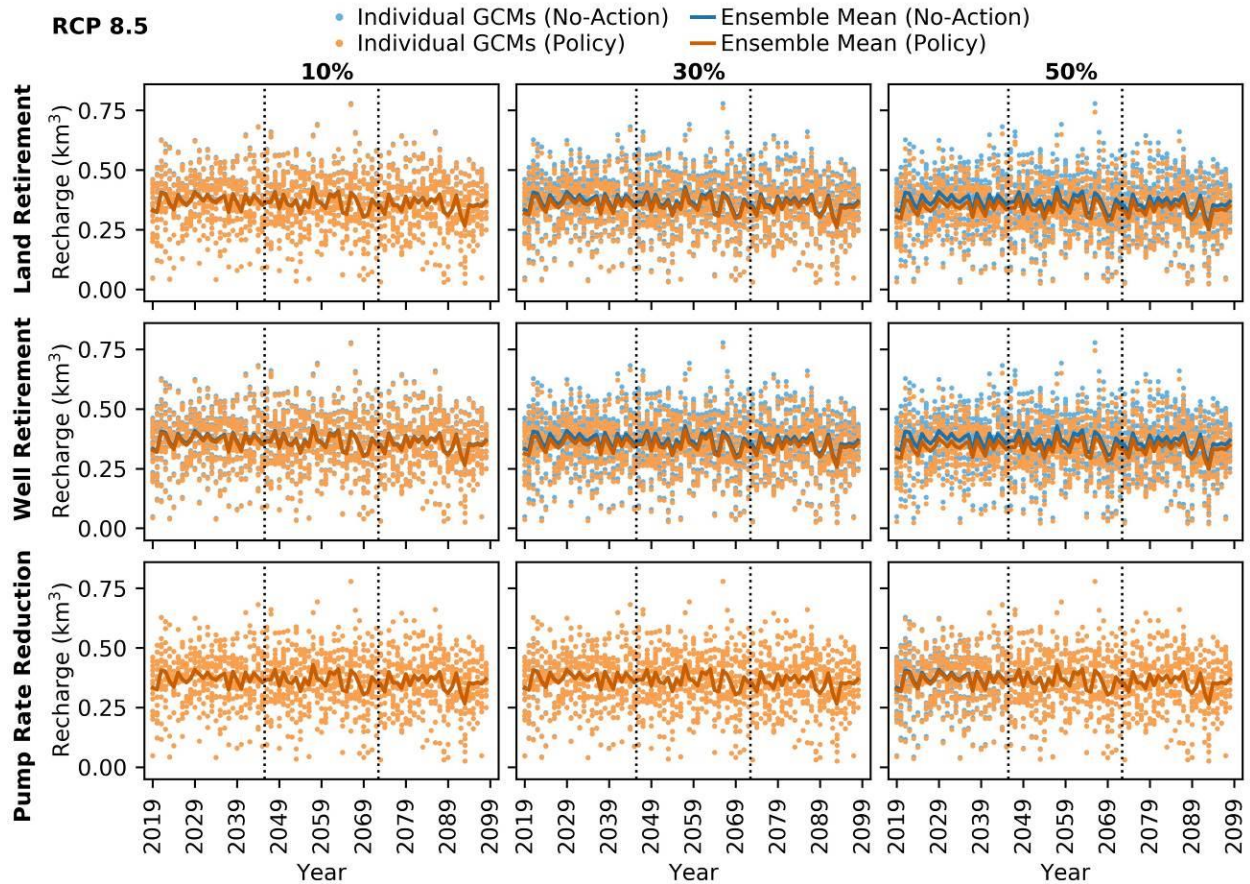


Figure C43. Total groundwater recharge in the study area as simulated by the ABM-MODFLOW, based on projections from an ensemble of global climate models (GCMs) for RCP8.5 under various management scenarios. Dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099).

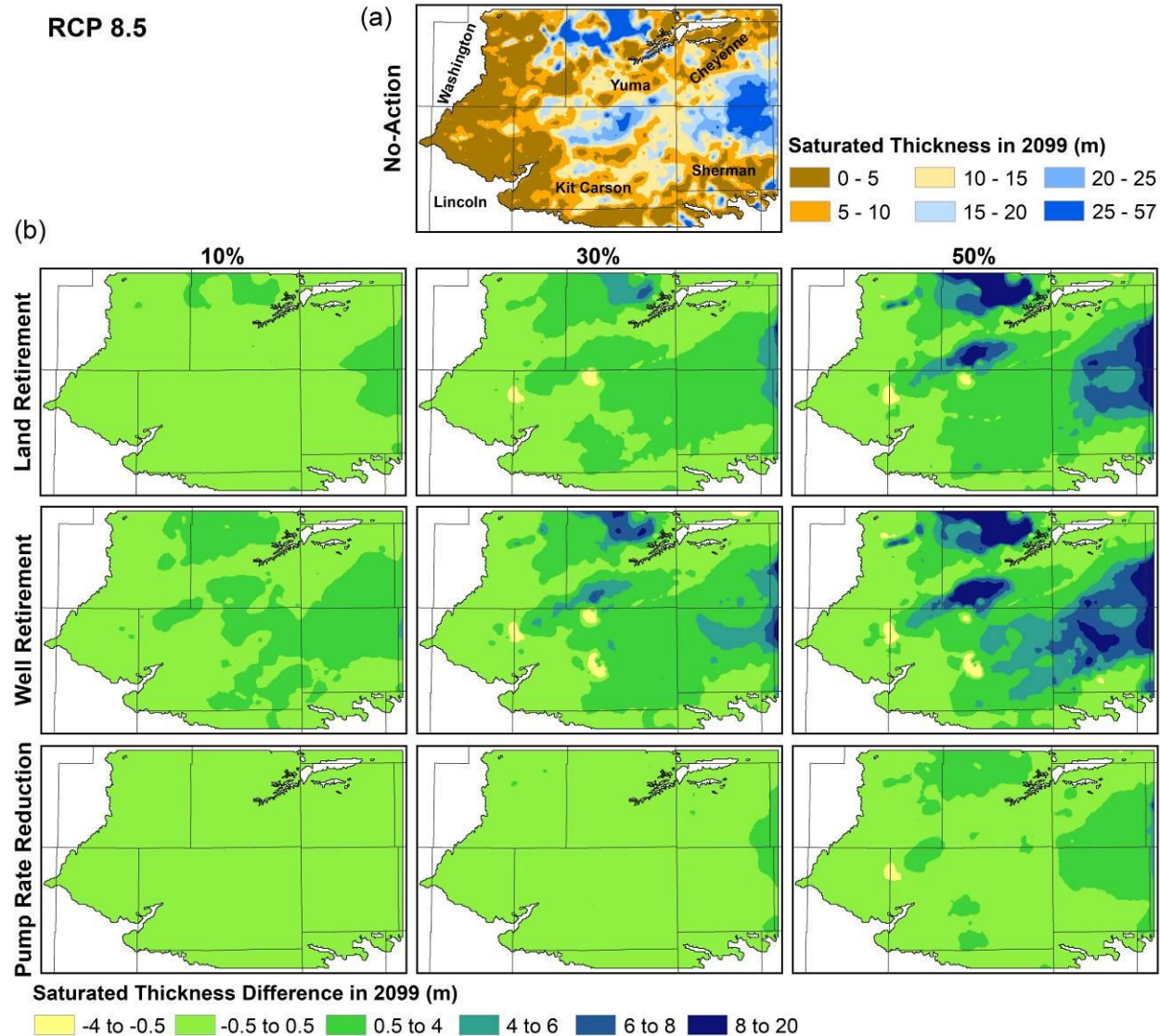


Figure C44. Influence of groundwater management policies on the aquifer's saturated thickness across the region under RCP8.5. (a) Saturated thickness in 2099 under the no-action scenario, calculated as the ensemble mean of simulation outcomes under climate projections from multiple global climate models (GCMs). (b) Change in saturated thickness in 2099, relative to the no-action scenario, under different groundwater management policies.

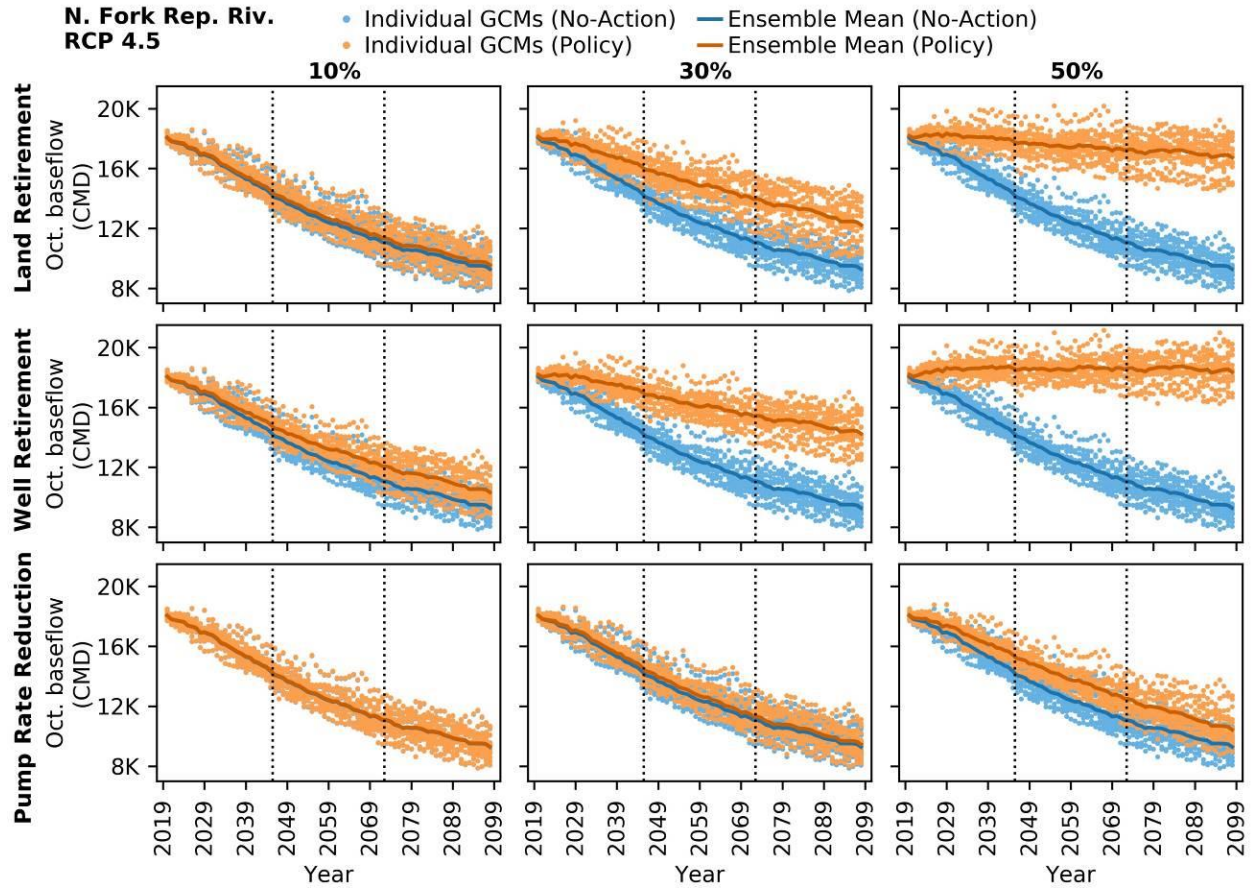


Figure C45. October average baseflows in the North Fork Republican River as simulated by the ABM-MODFLOW, based on projections from an ensemble of global climate models (GCMs) for RCP4.5 under various management scenarios. The location of the observation point is shown in Figure 1b. Dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099). CMD denotes cubic meters per day.

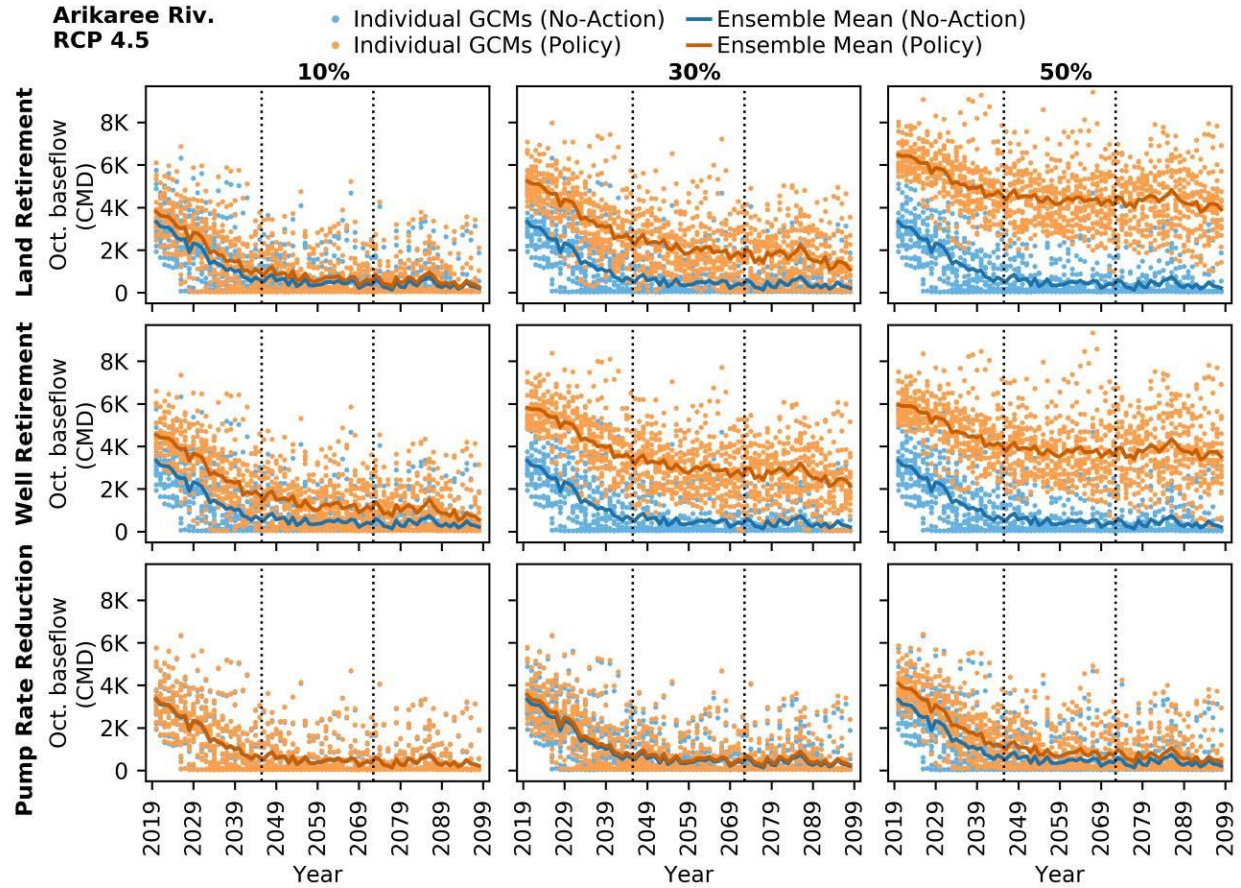


Figure C46. October average baseflows in the Arikaree River as simulated by the ABM-MODFLOW, based on an ensemble of global climate models (GCMs) projections for RCP4.5 under various management scenarios. The location of the observation point is shown in Figure 1b. Dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099). CMD denotes cubic meters per day.

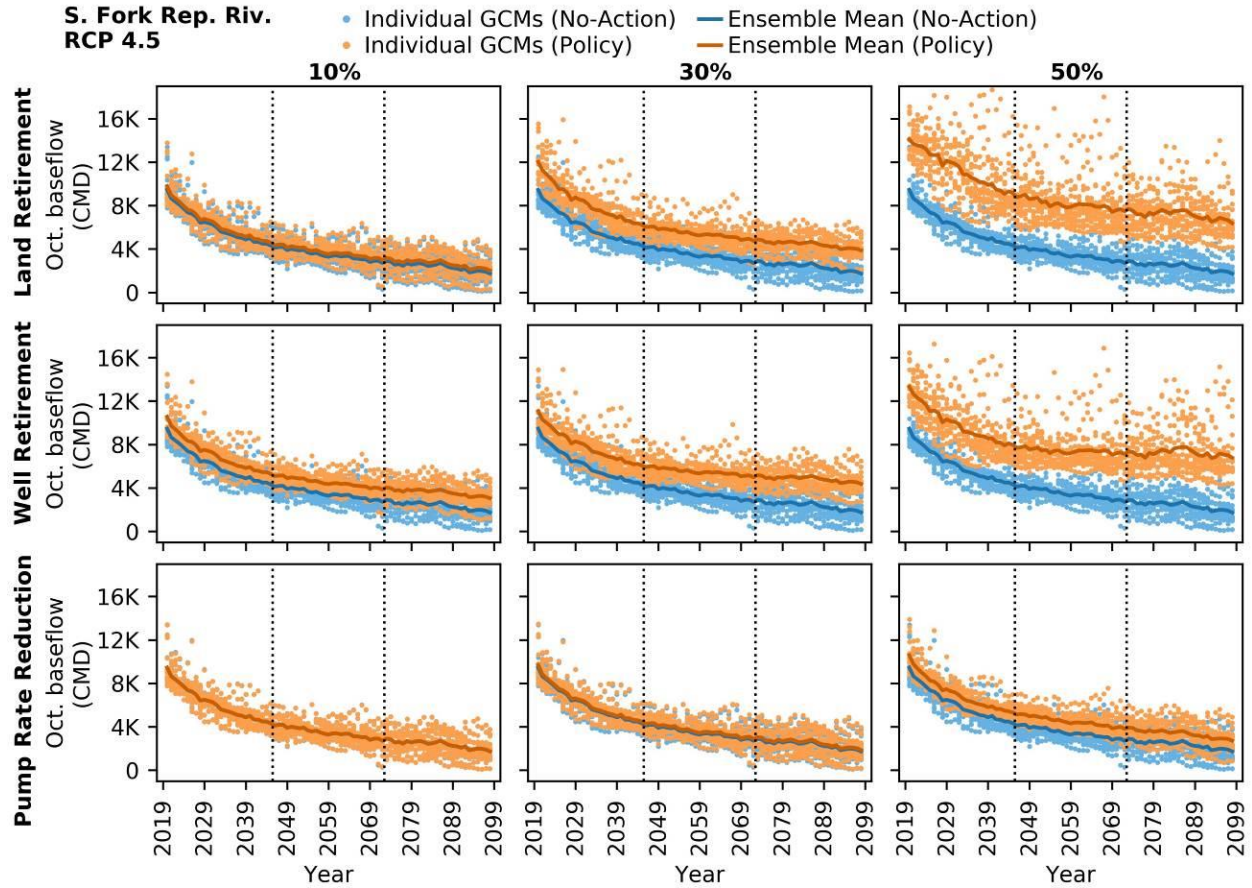


Figure C47. October average baseflows in the South Fork Republican River as simulated by the ABM-MODFLOW, based on an ensemble of global climate models (GCMs) projections for RCP4.5 under various management scenarios. The location of the observation point is shown in Figure 1b. Dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099). CMD denotes cubic meters per day.

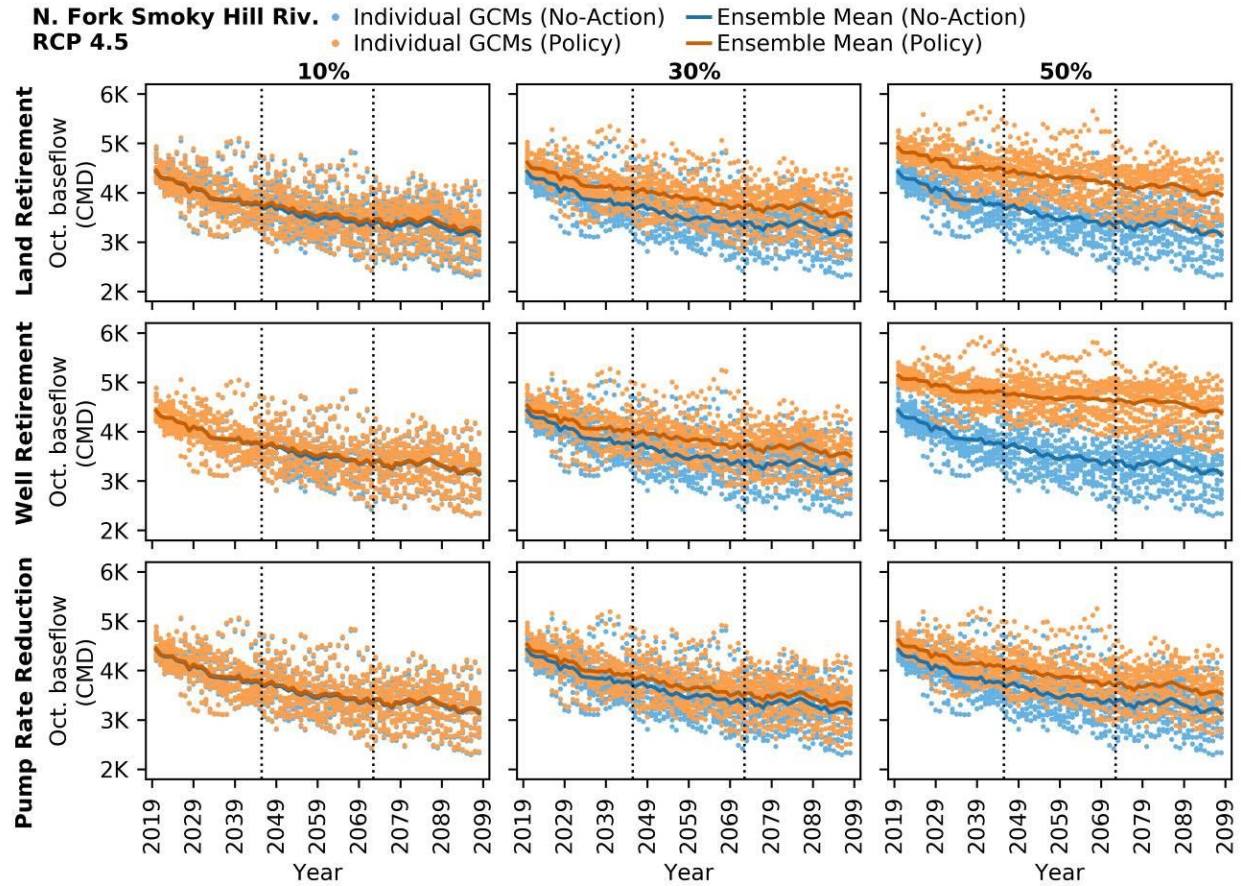


Figure C48. October average baseflows in the North Fork Smoky Hill River as simulated by the ABM-MODFLOW, based on an ensemble of global climate models (GCMs) projections for RCP4.5 under various management scenarios. The location of the observation point is shown in Figure 1b. Dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099). CMD denotes cubic meters per day.

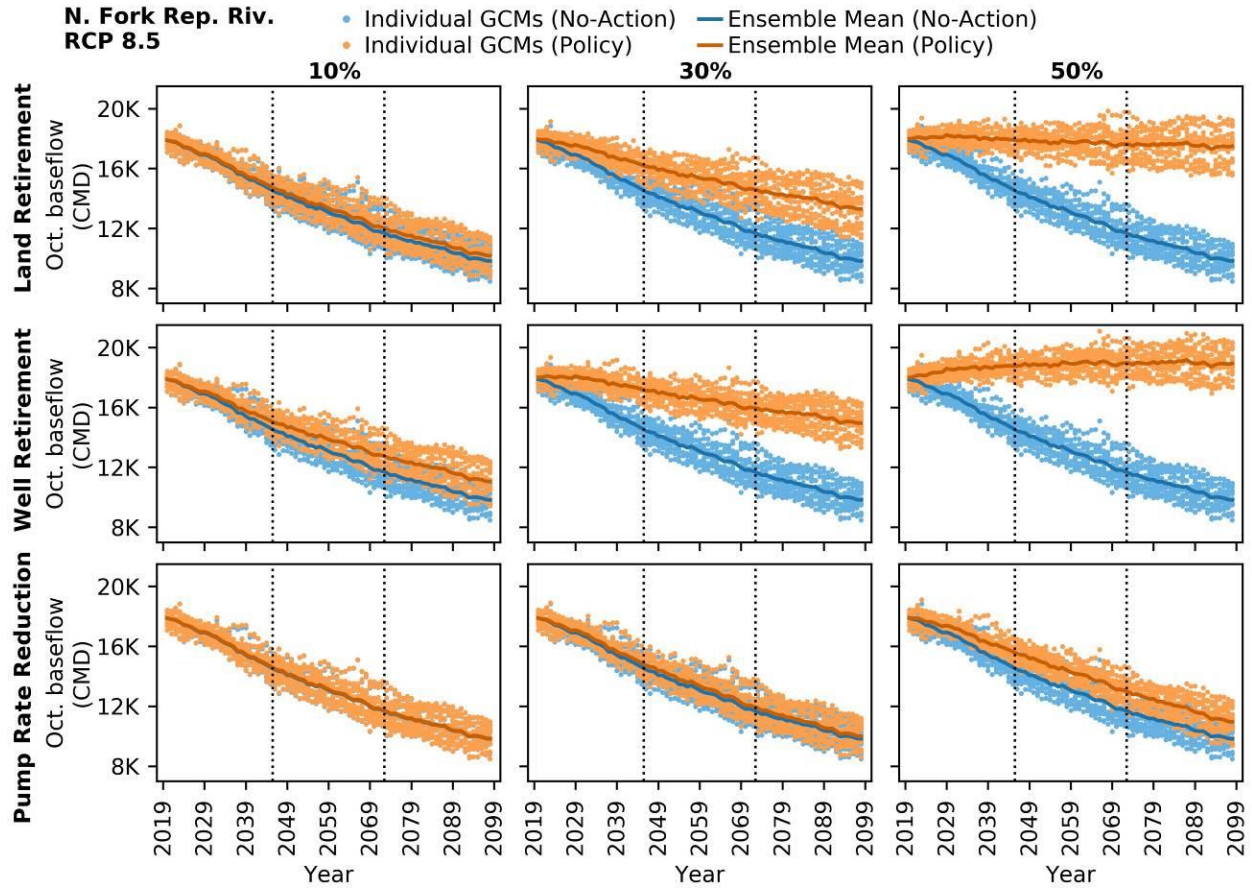


Figure C49. October average baseflows in the North Fork Republican River as simulated by the ABM-MODFLOW, based on projections from an ensemble of global climate models (GCMs) for RCP8.5 under various management scenarios. The location of the observation point is shown in Figure 1b. Dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099). CMD denotes cubic meters per day.

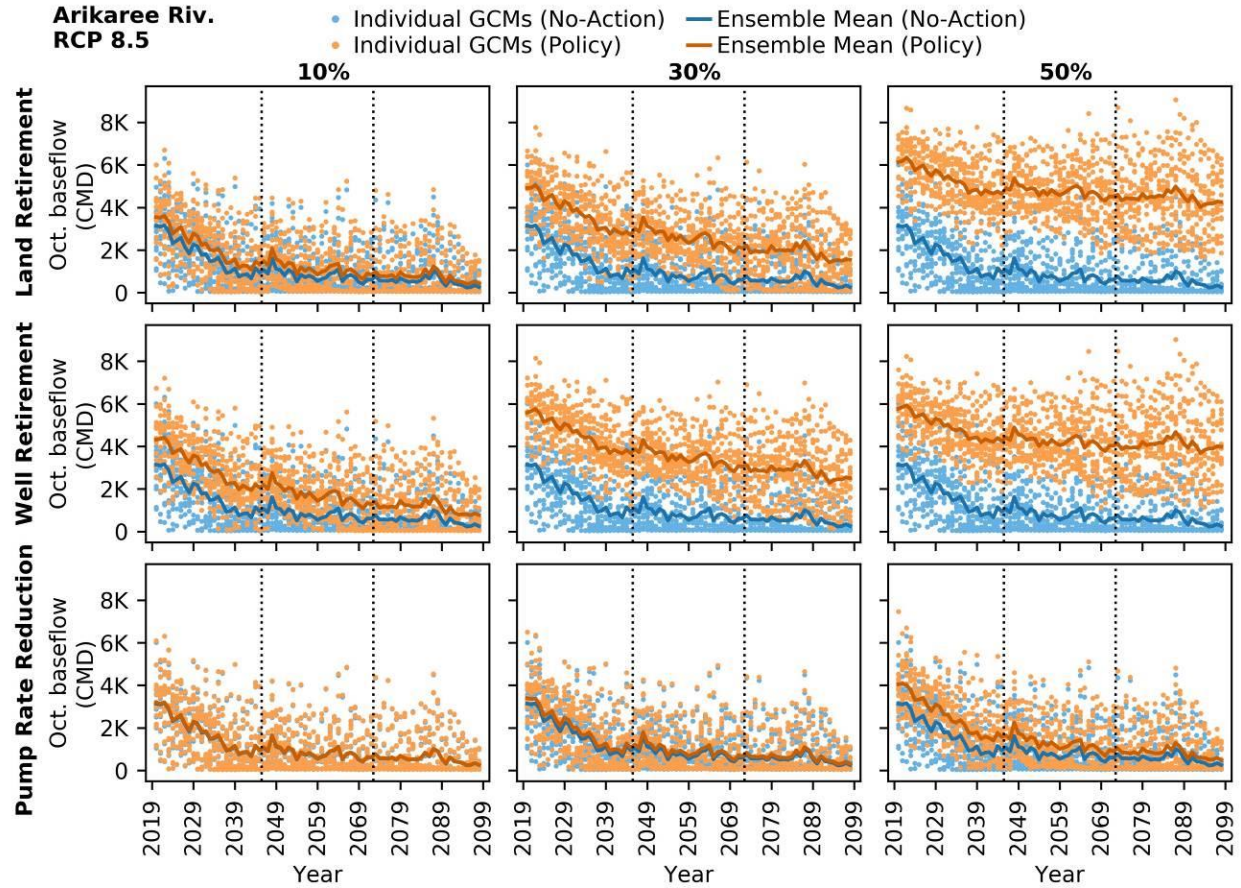


Figure C50. October average baseflows in the Arikaree River as simulated by the ABM-MODFLOW, based on an ensemble of global climate models (GCMs) projections for RCP8.5 under various management scenarios. The location of the observation point is shown in Figure 1b. Dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099). CMD denotes cubic meters per day.

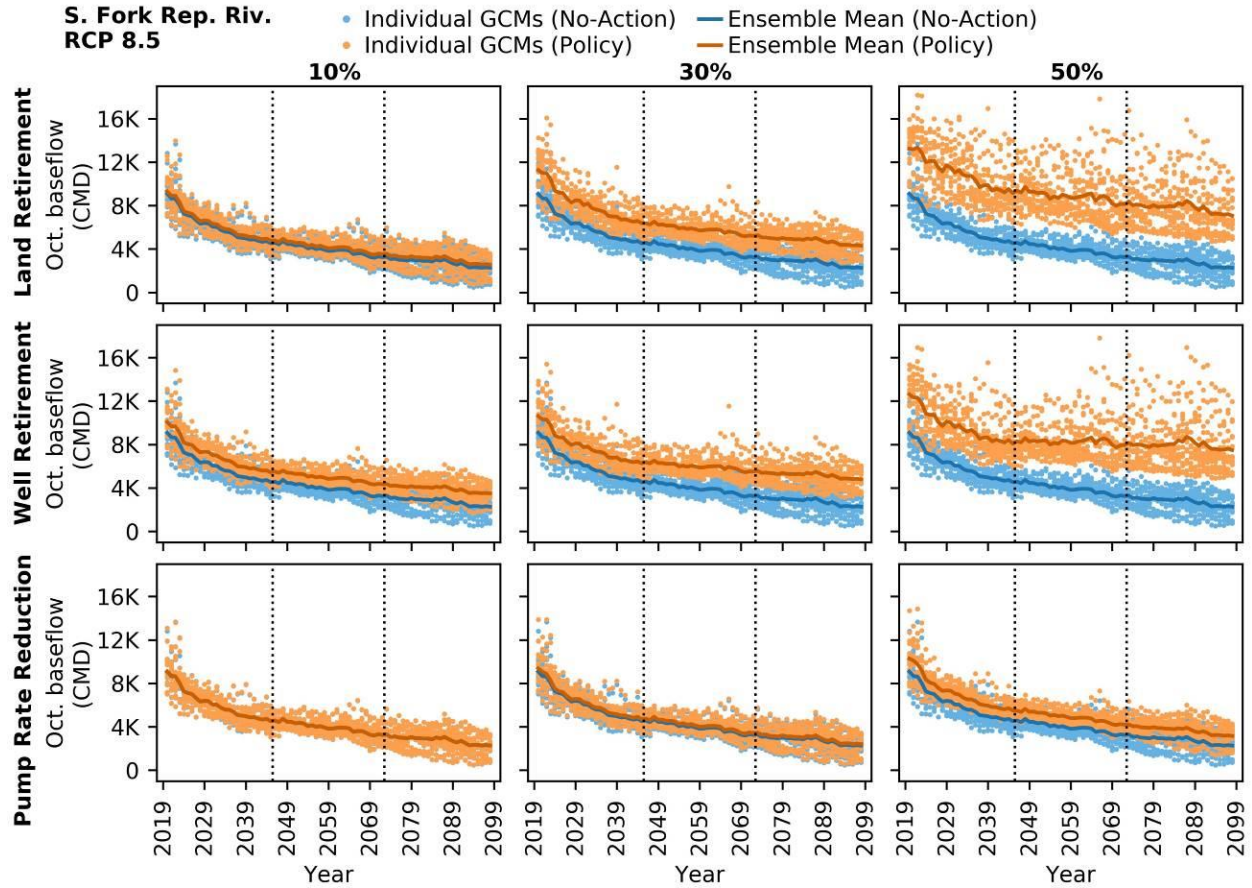


Figure C51. October average baseflows in the South Fork Republican River as simulated by the ABM-MODFLOW, based on an ensemble of global climate models (GCMs) projections for RCP8.5 under various management scenarios. The location of the observation point is shown in Figure 1b. Dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099). CMD denotes cubic meters per day.

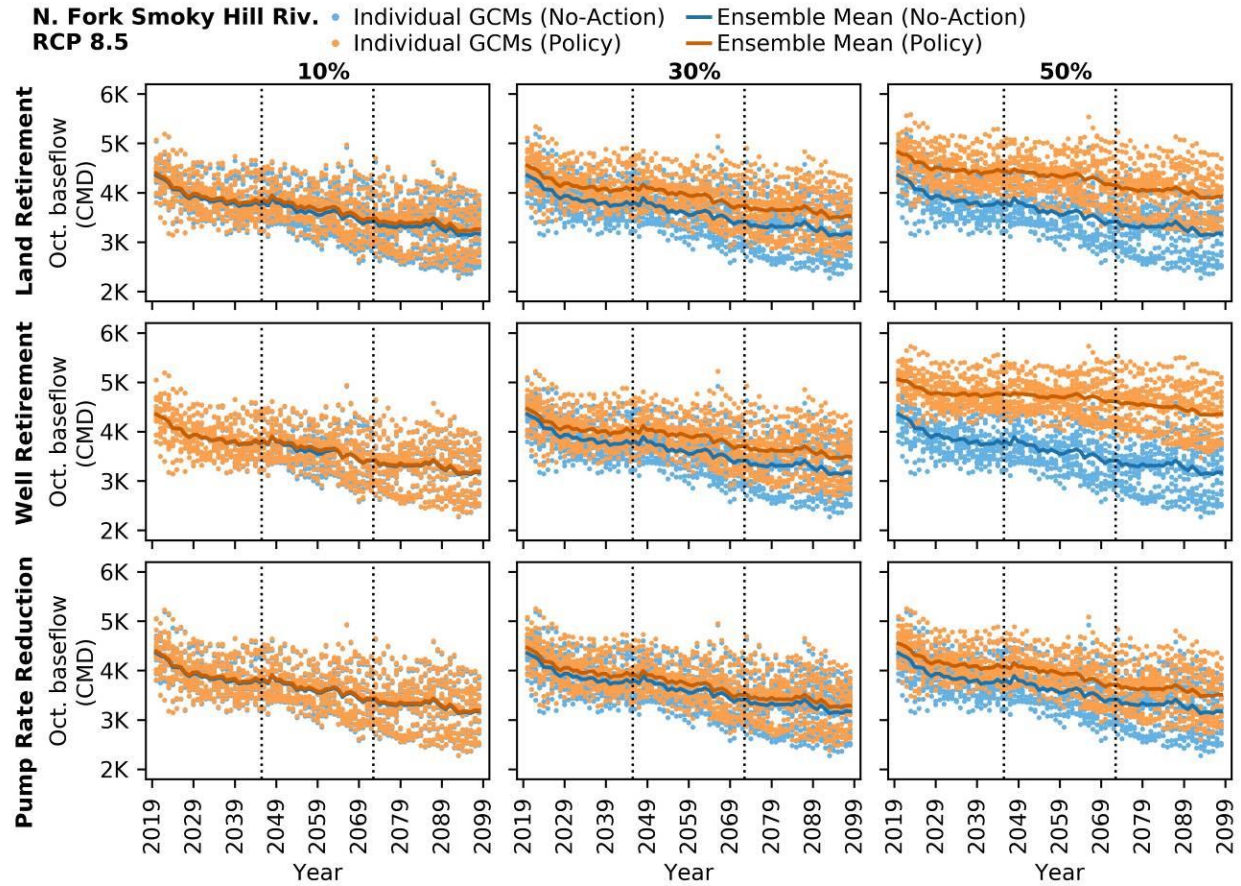


Figure C52. October average baseflows in the North Fork Smoky Hill River as simulated by the ABM-MODFLOW, based on an ensemble of global climate models (GCMs) projections for RCP8.5 under various management scenarios. The location of the observation point is shown in Figure 1b. Dotted lines mark the short-term (2019-2045), mid-term (2046-2072), and long-term projection periods (2073-2099). CMD denotes cubic meters per day.

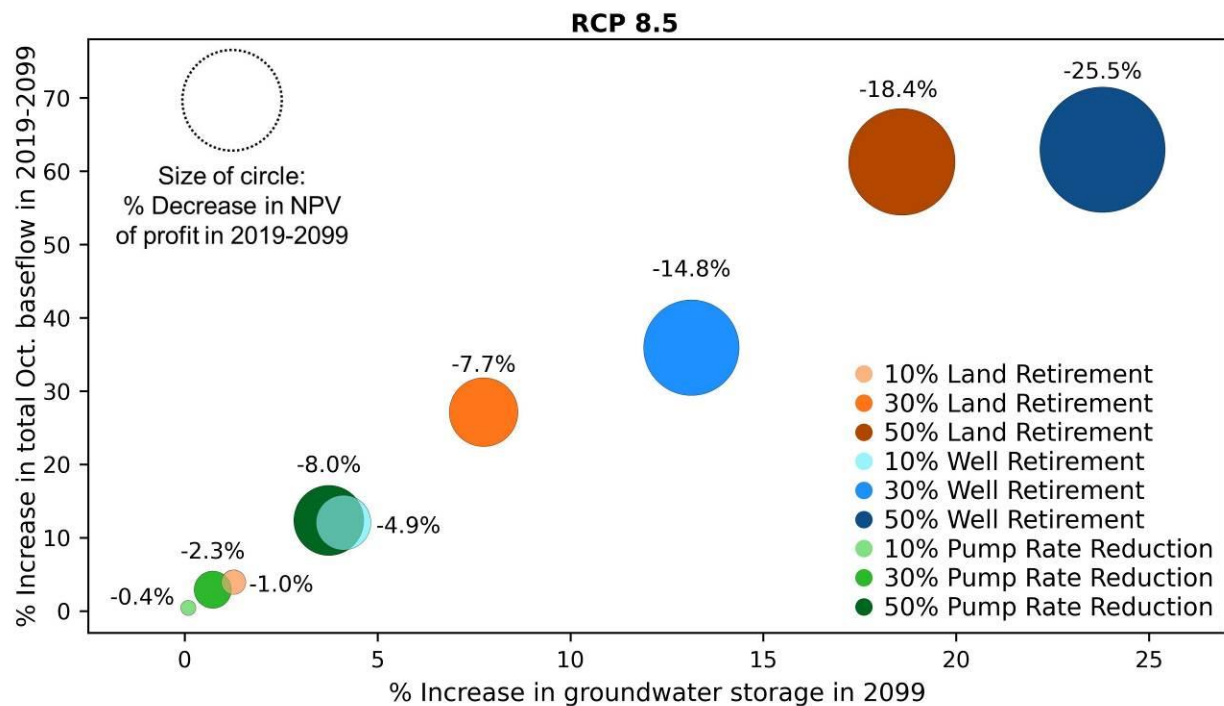


Figure C53. Comparison of region-wide policy outcomes under RCP8.5. All percent change values are calculated relative to the no-action scenario, based on the ensemble mean of simulation outputs from multiple global climate models (GCMs). NPV stands for net present value.

Table C1. Calibrated cultivar coefficients specified for corn and winter wheat in the agronomic model (DSSAT).

Parameter	Definition	Corn	Winter Wheat
P1	Thermal time from seedling emergence to the end of the juvenile phase during which the plant is not responsive to changes in photoperiod (°C days).	265	-
P1V	Days at the optimum vernalization temperature required to complete vernalization.	-	45
P1D	Percentage reduction in development when photoperiod is 10 hours shorter than the threshold, which is considered to be 20 hours, relative to that at the threshold.	-	50
P2	Extent to which development is delayed for each hour increase in photoperiod above the longest photoperiod at which development is at maximum rate, which is considered to be 12.5 hours (days).	0.4	-
P5	Thermal time from silking to physiological maturity (corn; °C days) or grain filling phase duration (winter wheat; °C days).	589	630
G1	Kernel number per unit canopy weight at anthesis (#/g).	-	21
G2	Maximum possible number of kernels per plant (corn; #) or standard kernel size under optimum conditions (winter wheat; mg).	908	25
G3	Kernel filling rate during the linear grain filling stage and under optimum conditions (corn; mg/day) or standard and non-stressed dry weight of a single tiller at maturity (winter wheat; g).	10	2
PHINT	Phylochron interval (°C days).	45	70

Source of data for corn is DeJonge et al. (2011) and for winter wheat is Elsayed et al. (2019).

Table C2. Prevalent soil types in groundwater-irrigated lands and their properties

Soil Name	Soil ID	Land Coverage (%) [*]	Depth (cm)	WP (cm/cm) ^{**}	FC (cm/cm) ^{**}	SWC (cm/cm) ^{**}	AWC (cm/cm) ^{**}	Ksat (cm/hr) ^{**}	BD (g/cm ³) ^{**}
Haxtun Sandy Loam	1	4.3	201	0.18	0.32	0.44	0.14	2.18	1.51
Julesburg Loamy Sand	2	3.2	152	0.13	0.26	0.40	0.13	14.32	1.25
Valent Sand	3	5.7	203	0.06	0.11	0.36	0.05	60.21	1.43
Ascalon Sandy Loam	4	3.2	203	0.14	0.23	0.40	0.09	4.85	1.25
Colby Silt Loam	5	2.5	152	0.16	0.33	0.50	0.17	3.30	1.39
Haxtun Loamy Sand	6	3.9	201	0.19	0.33	0.44	0.14	1.93	1.63
Kuma Keith Silt Loam	7	17.9	155	0.20	0.39	0.50	0.19	3.60	1.29
Norka Silt Loam	8	14.2	170	0.19	0.37	0.50	0.18	3.30	1.24
Richfield Clay Loam	9	2.4	201	0.20	0.38	0.50	0.18	0.81	1.38
Satanta Loam	10	6.0	152	0.18	0.34	0.47	0.16	3.30	1.23
Keith Silt Loam	11	19.6	201	0.17	0.36	0.48	0.19	2.28	1.23
Ulysses Silt Loam	12	6.9	201	0.17	0.35	0.50	0.18	3.30	1.25
Bridgeport Silt Loam	13	1.0	152	0.17	0.36	0.44	0.19	3.30	1.33
Kuma Silt Loam	14	6.4	201	0.21	0.45	0.49	0.24	1.63	1.51
Manter Sandy Loam	15	2.8	152	0.11	0.22	0.43	0.11	10.16	1.41

* Percentage of the total area of groundwater-irrigated parcels in 2018

** Weighted average calculated over 1 m depth, based on the thickness of soil layers

WP, wilting point; FC, field capacity; SWC, saturation water content; AWC, available water capacity; Ksat, saturated hydraulic conductivity; BD, bulk density. Source of data is SSURGO (Natural Resources Conservation Service, 2021).

Table C3. Management parameters specified for corn and winter wheat production.

Parameter	Corn	Winter Wheat
Conditions at Planting		
Planting Date	May 1	September 15
Planting Depth (cm)	5	5
Seeding Rate – Dryland (seeds/ha)	37,000	1,730,000
Seeding Rate – Irrigated (seeds/ha)	84,000	2,965,000
Seed Emergence (%)		95
Initial Soil Water Content (cm/cm)		0.13
Simulation Options		
Irrigation Application Depth (mm)		25
Irrigation Efficiency (%)*		85
Irrigation Management Depth (cm)		60
IFREQ (days)	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, and 25	
PAW _c (% of PAW)	25, 35, 45, 55, 65, and 75	
Reference Evapotranspiration Method	FAO Penman-Monteith equation (Allen et al., 1998)	

* Typical value for the center pivot irrigation system (Irmak et al., 2011), which is the dominant system in the study area.

Table C4. Economic model inputs.

Crop	Price (USD/tonne)*	Fixed Production Costs (USD/ha)**	Pumping Costs (USD/m ³)***
Irrigated Corn	182.79	910.56	0.03
Dryland Corn	182.79	443.95	0.00
Irrigated Winter Wheat	209.84	365.49	0.03
Dryland Winter Wheat	209.84	279.13	0.00

* Crop prices used here are the average of the 2010-2019 period to exclude the extreme volatility in crop prices experienced from 2007 to 2009.

** Costs are estimated based on the 2021 farm budgets (Kansas State University, 2021). Land rental and machinery ownership expenses are excluded from the calculations. Using the Farm Income and Wealth Statistics (Economic Research Service, 2021), the average government payment for each crop from 2010 to 2018 has been estimated and adjusted to 2021 USD values. This amount is then included as a subtrahend in the calculation of fixed production costs.

*** Including energy cost (computed using a well depth of 91 m and the average natural gas price from 2010 to 2019) plus repair costs in 2021 (Kansas State University, 2021).

Note. 1 tonne of corn is equal to 39.37 bu, 1 tonne of winter wheat to 36.74 bu, 1 ha to 2.47 ac, and 1 m³ to 0.0097 ac-in.

Table C5. Global climate models (GCMs) incorporated in the simulations, along with their resolution and associated institution.

GCM Model	Institution	Resolution (Long × Lat)
BCC-CSM1-1	Beijing Climate Center, China Meteorological Administration, China	2.8125° × 2.7906°
BCC-CSM1-1-m	Beijing Climate Center, China Meteorological Administration, China	2.8125° × 2.7906°
BNU-ESM	Beijing Normal University, China	2.8125° × 2.7906°
CanESM2	Canadian Center for Climate Modeling and Analysis, Canada	2.8125° × 2.7906°
CNRM-CM5	Centre National de Recherches Meteorologiques and Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique, France	1.40625° × 1.4008°
CSIRO-Mk3-6-0	Queensland Climate Change Centre of Excellence and Commonwealth Scientific and Industrial Research Organisation, Australia	1.875° × 1.8653°
GFDL-ESM2G	NOAA Geophysical Fluid Dynamics Laboratory, U.S.	2.5° × 2.0225°
GFDL-ESM2M	NOAA Geophysical Fluid Dynamics Laboratory, U.S.	2.5° × 2.0225°
HadGEM2-CC365	U.K. Met Office Hadley Centre, U.K.	1.875° × 1.25°
HadGEM2-ES365	U.K. Met Office Hadley Centre, U.K.	1.875° × 1.25°
INM-CM4	Russian Institute for Numerical Mathematics, Russia	2.0° × 1.5°
IPSL-CM5A-LR	Institut Pierre Simon Laplace, France	3.75° × 1.8947°
IPSL-CM5B-LR	Institut Pierre Simon Laplace, France	3.75° × 1.8947°
MIROC5	University of Tokyo, National Institute for Environmental Studies and Japan Agency for Marine-Earth Science and Technology, Japan	1.40625° × 1.4008°
MIROC-ESM	University of Tokyo, National Institute for Environmental Studies and Japan Agency for Marine-Earth Science and Technology, Japan	2.8125° × 2.7906°
MRI-CGCM3	Meteorological Research Institute, Japan	1.125° × 1.12148°

Table C6. Region-wide economic and environmental policy outcomes based on the ensemble mean of simulation outputs from multiple global climate models (GCMs) for RCP4.5 and RCP8.5.

Policy	RCP 4.5			RCP 8.5		
	NPV of profit in 2019-2099 (USD billion)	Groundwater storage in 2099 (km ³)	Total October baseflow in 2019-2099 (km ³)	NPV of profit in 2019-2099 (USD billion)	Groundwater storage in 2099 (km ³)	Total October baseflow in 2019-2099 (km ³)
No-Action	3.94	43.89	0.054	3.72	44.23	0.056
10% Land Retirement	3.90 (-0.97%)	44.37 (+1.11%)	0.056 (+3.74%)	3.68 (-0.96%)	44.79 (+1.27%)	0.058 (+3.93%)
30% Land Retirement	3.63 (-7.96%)	47.06 (+7.24%)	0.069 (+28.30%)	3.44 (-7.67%)	47.66 (+7.75%)	0.071 (+27.12%)
50% Land Retirement	3.18 (-19.35%)	51.92 (+18.31%)	0.088 (+64.35%)	3.03 (-18.44%)	52.45 (+18.59%)	0.090 (+61.26%)
10% Well Retirement	3.74 (-5.15%)	45.68 (+4.1%)	0.060 (+12.41%)	3.54 (-4.86%)	46.05 (+4.12%)	0.062 (+12.06%)
30% Well Retirement	3.32 (-15.70%)	49.65 (+13.15%)	0.074 (+37.62%)	3.17 (-14.81%)	50.04 (+13.14%)	0.076 (+35.91%)
50% Well Retirement	2.87 (-27.09%)	54.41 (+23.99%)	0.089 (+64.98%)	2.77 (-25.50%)	54.75 (+23.79%)	0.091 (+62.92%)
10% Pump Rate Reduction	3.93 (-0.40%)	43.92 (+0.08%)	0.054 (+0.32%)	3.71 (-0.37%)	44.27 (+0.09%)	0.056 (+0.41%)
30% Pump Rate Reduction	3.85 (-2.44%)	44.21 (+0.74%)	0.055 (+2.86%)	3.64 (-2.25%)	44.55 (+0.73%)	0.057 (+2.89%)
50% Pump Rate Reduction	3.60 (-8.68%)	45.6 (+3.92%)	0.061 (+13.12%)	3.42 (-7.97%)	45.88 (+3.74%)	0.063 (+12.34%)

Note: NPV stands for net present value and is calculated using a 5% discount rate. Values presented in parentheses represent the percent change compared to the no-action scenario.

Table C7. Effects of the discount rate on net present value (NPV) of region-wide profit projected under different management scenarios.

Policy	RCP 4.5			RCP 8.5		
	NPV of profit in 2019-2099 (USD billion)	NPV of profit in 2019-2099 (USD billion)	NPV of profit in 2019-2099 (USD billion)	NPV of profit in 2019-2099 (USD billion)	NPV of profit in 2019-2099 (USD billion)	NPV of profit in 2019-2099 (USD billion)
	3% discount rate	5% discount rate	7% discount rate	3% discount rate	5% discount rate	7% discount rate
No-Action	5.73	3.94	3.00	5.63	3.72	2.76
10% Land Retirement	5.68 (-0.87%)	3.90 (-0.97%)	2.97 (-1.04%)	5.58 (-0.92%)	3.68 (-0.96%)	2.74 (-0.99%)
30% Land Retirement	5.32 (-7.12%)	3.63 (-7.96%)	2.74 (-8.58%)	5.24 (-6.97%)	3.44 (-7.67%)	2.54 (-8.17%)
50% Land Retirement	4.71 (-17.74%)	3.18 (-19.35%)	2.39 (-20.49%)	4.68 (-16.87%)	3.03 (-18.44%)	2.22 (-19.52%)
10% Well Retirement	5.46 (-4.67%)	3.74 (-5.15%)	2.84 (-5.50%)	5.39 (-4.30%)	3.54 (-4.86%)	2.62 (-5.26%)
30% Well Retirement	4.90 (-14.39%)	3.32 (-15.70%)	2.50 (-16.61%)	4.88 (-13.25%)	3.17 (-14.81%)	2.32 (-15.91%)
50% Well Retirement	4.29 (-25.11%)	2.87 (-27.09%)	2.15 (-28.48%)	4.33 (-23.04%)	2.77 (-25.50%)	2.01 (-27.22%)
10% Pump Rate Reduction	5.71 (-0.33%)	3.93 (-0.40%)	2.99 (-0.46%)	5.61 (-0.29%)	3.71 (-0.37%)	2.75 (-0.44%)
30% Pump Rate Reduction	5.61 (-2.01%)	3.85 (-2.44%)	2.92 (-2.76%)	5.53 (-1.76%)	3.64 (-2.25%)	2.69 (-2.64%)
50% Pump Rate Reduction	5.31 (-7.28%)	3.60 (-8.68%)	2.71 (-9.72%)	5.27 (-6.40%)	3.42 (-7.97%)	2.51 (-9.16%)

Note: Values presented in parentheses represent the percent change compared to the no-action scenario.