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Platte River Basin Water Resources II

Predicting Land Cover Change in the Platte River Basin to Select Wetland Protection Sites Vulnerable to Urban Encroachment

DEVELOP Technical Report
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Nancee Uniyal (Project Lead)
Olivia Kirkland
Shaibal Ahmed
Yulia Shaffer

Advisor:
Dr. Marguerite Madden, University of Georgia, Center for Geospatial Research (Science Advisor)

Previous Contributors:
Jennifer Mathis
Jackie Encinas
Olivia Kirkland
Emma Vail

Lead:
Megan Rich (Georgia – Athens)

1. Abstract
The Platte River Basin (PRB) represents a critical dynamic ecosystem where wetlands play a pivotal role as essential habitats for local and migratory birds, as well as various flora and fauna. It also provides many crucial ecosystem services that directly and indirectly benefit human welfare. However, it is threatened by anthropogenic activity, climate change, and urbanization. Our team partnered with Audubon Great Plains, the regional office of a national non-profit organization, to analyze the future potential development of the region and its potential impact on the wetlands. We utilized remotely sensed data, such as Landsat 8 Operational Land Imager and Suomi National Polar Orbiting Partnership Visible Infrared Imaging Radiometer Suite, as well as NASA Socioeconomic Data and Application Center data, to simulate urban growth potential up to 2050 using the open-source FUTure Urban-Regional Environment Simulation model. Our results for two proposed scenarios (all wetlands are protected, and no wetlands are protected) revealed that at least 56 counties out of 81 in the PRB would experience growth by the year 2050. The results for the first scenario show that there will be no loss of wetlands in the future. However, the results for the second scenario indicate a basin-wide reduction of 43.22 square kilometers (0.58%) in wetland areas, leading to a significant loss of bird habitat, critical for conservation. The results will help Audubon Great Plains' Urban Woods and Prairies Initiative to lead awareness workshops for communities about wetland protection and to form impactful conservation strategies.

Key Terms
FUTURES, urban growth model, Platte River Basin, urban development, wetland loss, land use/land cover change

2. Introduction
2.1 Background Information
Wetlands, often called "nurseries of life," are ecological systems that serve as vital habitats for biodiversity (U.S. Environmental Protection Agency [EPA], 2004). They provide essential ecosystem services that directly and indirectly contribute to human welfare, including regulating services (such as water filtration, flood and erosion control, microclimate regulation) and supporting services (e.g., nutrient cycling, water conservation, carbon sequestration; Chatterjee et al., 2015; Loiselle et al., 2023; Kadykalo et al., 2021). For example, when rivers overflow, wetlands absorb the excess water and slow down the floodwaters, preventing damages to the built environment (U.S. EPA, 2004). However, wetlands are among the most vulnerable ecosystems, facing threats from climate change, human activity, and urbanization (Salimi et al., 2021; Xiong et al., 2023; Johnson et al., 2013; Lee et al., 2006). These pressures degrade the quality and functionality of wetlands, reducing their ability to provide these vital services and impacting both ecological health and human well-being.

The Platte River Basin (PRB), spanning Nebraska, Colorado, and Wyoming, covers approximately 222,740 square kilometers (about 86,000 square miles; Figure 1). Its wetlands serve as vital habitats and prominent migratory and breeding stopovers for hundreds of bird species including endangered whooping cranes, piping plovers, and interior least terns (National Research Council, 2005). Protecting and restoring these threatened wetlands is critical for addressing impacts of climate change, particularly concerning carbon and nutrient cycles, climate adaptation, and mitigation (Moomaw et al., 2018). Understanding and predicting how these wetlands respond to stressors is crucial in developing effective long-term land management strategies (Mantyka-Pringle et al., 2014).

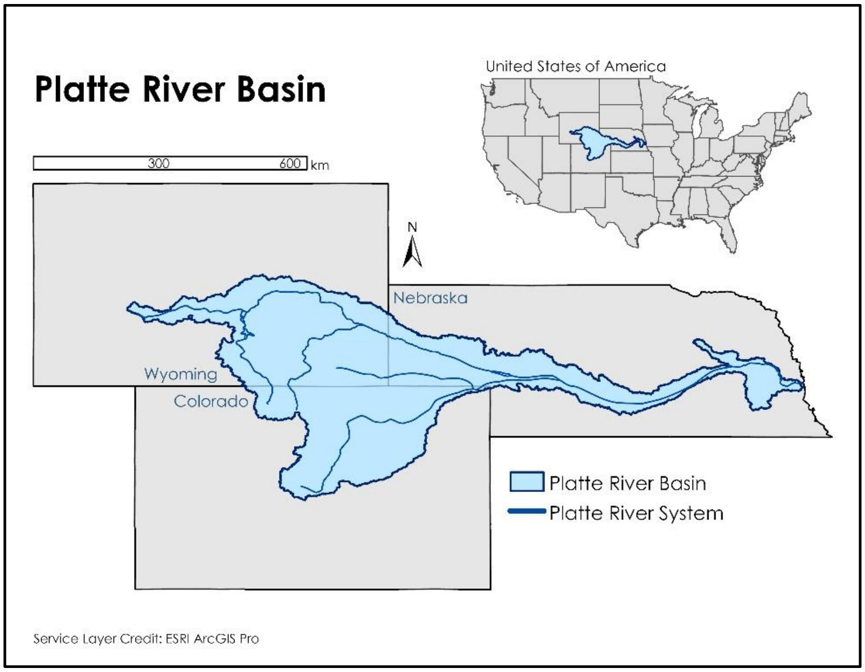

Figure 1. Map showing the Platte River Basin.

Remote sensing products and tools are reliable and powerful methods for assessing physical environmental changes over time, including observing urban growth and riparian areas (Kamran & Yamamoto, 2023; Lechner et al., 2020). Using remote sensing imagery provides a strong foundation for understanding patterns and trends of temporal land use/land cover (LULC) change in the PRB. Urban growth models (UGMs), which utilize area-specific parameters such as remote sensing inputs to forecast future growth patterns, are valuable for developing long-term strategies for wetland ecosystem protection and restoration (Wang et al., 2024; Yao et al., 2016). The Future Urban-Regional Environment Simulation (FUTURES) model is a versatile UGM capable of large-scale processing, making it highly suitable for the PRB (Meentemeyer et al., 2013; Van Berkel et al., 2019). Similar to our study, FUTURES has been used to analyze the impacts of potential urban encroachment on habitat fragmentation and ecosystem services, demonstrating how conservation initiatives can incorporate this information into their strategies (Van Berkel et al., 2019; Pickard et al., 2016; Dorning et al., 2015). To pursue this objective, we partnered with Audubon Great Plains (AGP) to study spatiotemporal LULC changes within the PRB from 2001 to 2021, then used these change trends as well as other suitability parameters and major drivers to forecast LULC change patterns for 2030, 2040, and 2050, resulting in a study period of 50 years.

2.2 Project Partners and Objectives

Audubon Great Plains (AGP) is the regional office of the National Audubon Society for Nebraska, North Dakota, and South Dakota. The organization uses science, habitat restoration, outreach, and education to address core threats to birds in the region. AGP's mission is to preserve native and migratory bird habitats to protect endangered species for the present and the future. AGP reaches millions of people annually through its state programs, local chapters, and nature centers. Our partners recognize that developing adaptive wetlands management strategies supported by a solid scientific foundation is essential for maintaining biodiversity and ensuring the resilience of this vital natural resource against future environmental challenges and anthropogenic pressures.

In the previous term of the project, the team used Landsat 8 Operational Land Imager (OLI) and Sentinel-2 Multispectral Instrument (MSI) to 1) assess LULC change within both the Central Platte River Basin from 2013 to 2023 and thirteen priority cities from 2019 to 2023 and 2) depict flood risk for one priority city using an extreme flood event in 2019. Results showed a basin-wide decrease in agriculture, vegetation, and grassland coverage. One focal city, Grand Island, NE, tripled in percentage of urban coverage, making it a prime candidate for restoration efforts. Their recommendations for future work included using a UGM to forecast LULC change to predict future vulnerabilities.

The objective of this project's second term was to assess the feasibility of using Landsat imagery and FUTURES to highlight potential restoration sites in support of our partner's goal to protect wetland areas vulnerable to urbanization. Additionally, we aimed to predict LULC change in the PRB to inform selection of wetland protection sites vulnerable to urban encroachment. To accomplish this, we projected LULC change into 2030, 2040, and 2050 to produce wetland vulnerability maps and examine the impact of future urbanization on wetlands in the PRB.

3. Methodology

Our team developed a replicable methodology for forecasting urban growth and analyzing its impact on wetland areas. We utilized Landsat 8 OLI and Suomi-National Polar Orbiting Partnership (NPP) Visible Infrared Imaging Radiometer Suite (VIIRS) imagery to generate a Normalized Difference Vegetation Index (NDVI) and Nighttime Lights data, respectively. We integrated these datasets, along with additional supplemental data, to create a comprehensive database for training the FUTURES model. Using these inputs for the simulation, we generated final maps and GeoTIFFs depicting potential urban growth in the PRB. Subsequently, we conducted statistical and wetland vulnerability analyses to quantify forecasted LULC changes and assess the extent of potential wetland degradation. These analyses offered valuable insights into areas where restoration efforts can be prioritized to protect vulnerable wetland regions.

3.1 Data Acquisition

3.1.1 LULC Data

To run the FUTURES UGM, we acquired National Land Cover Database (NLCD) datasets from Google Earth Engine (GEE). The FUTURES model requires precise projections of land consumption at subregional levels for data training (Dewitz & United States Geological Survey, 2021; Dewitz, 2023). These projections were essential for determining the amount of land area to be converted over specific time intervals and for effectively reducing assumptions of stationarity in the model.

For land consumption input, either the NLCD or a custom classification can be utilized. We selected the NLCD because it ensures that the LULC classification is consistent and reliable over an extended period. By analyzing changes in existing maps, such as the NLCD, we obtained accurate inputs for land conversion. This enhanced the precision and effectiveness of the model in urban growth analysis. We selected 5-year increment data, rather than selecting data from every consecutive year within our time range, to reduce processing time in FUTURES. We chose this approach assuming 5-year intervals are sufficient to capture noticeable LULC change (Kii, 2021).

3.1.2 NDVI

Urban development generally negatively impacts the quality and quantity of vegetation (Zhang et al., 2022). We incorporated an NDVI to delineate vegetation and vegetation stress, which has previously been used for studies in agriculture and LULC change (United States Geological Survey [USGS], n.d., Huang et al., 2021). To evaluate changes in vegetation health in the PRB, we collected Landsat 8 OLI data from GEE and derived NDVI values (Equation 1). Higher NDVI values typically correspond to healthier vegetation (Martinez & Labib, 2023). To enhance our predictions, we integrated NDVI into the FUTURES UGM for data training purposes.

$$\text{NDVI} = \frac{\text{NIR - R}}{\text{NIR + R}} \tag{1}$$

Equation 1. NDVI calculation. NIR – Near infrared, R – Red bands. (Kriegler et al., 1969)

3.1.3 Census Data and Population Projections

The DEMAND sub-model in the FUTURES UGM quantifies per capita land demand across different subregions. It essentially determines how much land will be required for future scenarios of urbanization based on projected population data. By analyzing spatiotemporal land use patterns, the model establishes the relationship between population growth and development demand. For each historical time step (2001, 2006, 2011, 2016, and 2021), we utilized county-level population totals obtained from the National Historical Geographic Information Systems (NHGIS) and U.S. Census Bureau to analyze changes over time, providing insight into how population change impacts land use (Manson et al., 2023).

The model not only uses historical data as a non-stationary time series parameter but also incorporates future population projections to predict land use needs. These projections help the model estimate the demand for land as the population grows. To support this, we acquired annual population growth projections by county for every 5-year interval from 2025 to 2050 from the NASA Socioeconomic Data and Applications Center (SEDAC; Hauer, 2021).

3.1.4 TIGER/Line Study Area Boundaries

As part of the stationary time series parameters essential for performing FUTURES analysis, we included study area boundaries, which encompassed state and county borders obtained from Topologically Integrated Geographic Encoding and Referencing (TIGER)/Line Shapefiles. This was important for setting the spatial extent of the study area. Additionally, we incorporated data on physical characteristics, such as roads, hydrology, and major cities, obtained from the same data source. These datasets served as predictors in the training of the FUTURES model.

3.1.5 Digital Elevation Model

Slope gradient is also one of the predicting stationary time series parameters of development potential used in the FUTURES UGM. To obtain these data, we acquired a Digital Elevation Model (DEM) raster pertaining to our study area from the USGS 3D Elevation Program (3DEP). The DEM data help in understanding the topographical features of the region, which can significantly influence urban expansion patterns. We incorporated these data for more accurate modeling of potential growth areas, to ensure we accounted in our projections for physical land constraints.

3.1.6 Nighttime Lights Data/VIIRS

Further, in our dataset for the model, we included NASA's Nighttime Lights data from the VIIRS sensor on the Suomi-NPP satellite. Its Day/Night Band (DNB) collects global low-light imaging data that captures electric lighting from human settlements on Earth's surface (Elvidge et al., 2017). We included Nighttime Lights data from 2021 as a supporting stationary dataset to complement our non-stationary data, such as LULC, to confirm the most populous and developed areas within the PRB.

3.1.7 Protected Areas/PAD-US

Another parameter that we included in the FUTURES simulation model is protected areas acquired from the USGS Protected Areas Database of the United States (PAD-US). These data provide information about protection statuses of parks and open spaces across the United States, utilizing three different Gap Analysis Project (GAP) status classes: disturbance allowed, disturbance suppressed, extraction allowed. We needed these data to mask protected areas in the FUTURES data training, ensuring that these land use classes are not considered for future development.

Table 1

Datasets, descriptions, and purpose for gathering, for which years they were acquired, and sources.

Dataset	**Description / Purpose**	**Years Acquired**	**Source**

NDVI	Normalized Difference Vegetation Index/used for assessing vegetation health and change	2021	GEE, Landsat 8 OLI
NLCD	Comprehensive, national LULC data	2001, 2006, 2011, 2016, 2021	USGS, GEE
Population data	Total population estimations	2001, 2006, 2011 2016, 2021	IPUMS NHGIS U.S. Census Bureau
Population projections	County-level population projections	2025, 2030, 2035, 2040, 2045, 2050	NASA SEDAC
Study area boundaries and inventory	Shapefiles of study area boundaries (states, counties, census tracts), inventory (roads, water lines and water areas, urban centers)	2023	U.S. Census Bureau TIGER/Line
Digital Elevation Model	1-arc DEM for slope analysis of the study area (approx. 30-meter resolution)	2021, 2022, 2023	USGS, 3DEP
Nighttime Lights	Remotely senses lights at night	2021	NASA's Black Marble, VIIRS of Suomi NPP
Protected area	Protected Areas Database of the United States, an official inventory of public parks and protected open space		PAD-US, USGS

3.2 Data Processing

3.2.1 Normalized Difference Vegetation Index

After acquiring the data, we processed the necessary raw data to prepare for analysis. We calculated NDVI in GEE by first filtering the imagery according to our study area boundary, then by dates from June 1, 2021, to September 30, 2021. We also filtered the data by removing imagery with cloud cover greater than 20%. Then, we calculated the median value at each pixel across the entire image collection. To calculate the NDVI we extracted two bands, near infrared and red, and calculated the ratio between the two (Equation 1). The final NDVI product was a simplified image, derived as a single band (Kriegler et al., 1969; Huang et al., 2021).

3.2.2 Ancillary Data

For processing the population and population projection data, we extracted the totals for all years of interest by the counties within the study area and compiled them in a table. To delineate the boundaries of the counties within the PRB region, we processed the data in ArcGIS Pro, which resulted in the selection of 81 counties. We did similar data processing for the physical characteristics, such as roads, hydrology, and major cities. Additionally, to incorporate the slope gradient as a stationary parameter in the FUTURES simulation, we prepared and processed the DEM raster inputs in ArcGIS Pro using the Mosaic to New Raster tool, which allowed us to combine all the images and filter them by the study area. Furthermore, we also clipped PAD-US data to our study area, focusing specifically on GAP Status 1 and GAP Status 2. This selection was made because GAP Status 1 represents areas managed for biodiversity, where natural disturbance is allowed to proceed or is mimicked by management, ensuring minimal human interference. GAP Status 2, however, includes areas also managed for biodiversity, but where natural disturbance is suppressed. By concentrating on these categories, we were able to accurately identify and protect regions with the highest conservation value, ensuring that the FUTURES model reflects environmental constraints within our study area (USGS, 2024).

3.2.3 Nighttime Lights

The Nighttime Lights data from Suomi-NPP VIIRS had a much lower resolution of 463.83 meters, which was coarser than the rest of our input data. Due to this discrepancy, it was necessary to adjust the resolution for consistency in our analysis. After downloading the data, we resampled it in ArcGIS Pro to a finer resolution of 30 meters, aligning it with the resolution of the NDVI and LULC datasets.

3.2.4 Preparing the Database in GRASS GIS

Once we set up the Geographic Resources Analysis Support System (GRASS) GIS environment, we imported our datasets into a GRASS GIS database. The computational region was set to the extent of the study area. We aligned the cells by using one of the LULC layers as a reference, ensuring that all subsequent spatial analyses were consistent with the existing raster data.

We derived predictors for our model from our datasets. The predictors included slope, distance to protected areas, distance to lakes/water, distance to roads, distance to city centers, forest, NDVI, and the Nighttime Lights data. The slope, derived from the DEM, indicated areas where steeper slopes may be less suitable for development. Areas near protected areas, including lakes or water, can attract urban growth due to their scenic appeal (Radeloff et al., 2010). Between 1940 and 2000, 28 million housing units were developed within 50 km from protected areas; 940,000 houses were built near national forests, with at least 20% by 1990 built within 1 km of protected areas (Radeloff et al., 2010). Road density and proximity to city centers are strong indicators of potential urban development. Dense road networks in suburban areas facilitate development, while city centers act as hubs for concentrated population and economic activities (Zhao et al., 2017). Forests and healthy vegetation both have positive effects on urban growth because they attract residents who seek proximity to natural green spaces as desirable living environments (Jung, 2023). The Nighttime Lights data were also added as a driver of urban growth because illuminated places indicate proximity to urban areas and can influence future urban development.

3.3 Data Analysis

3.3.1 FUTURES Simulations

We defined two distinct scenarios to explore the impacts of wetland protection on urban growth using NLCD data. The NLCD provides detailed land cover information, which we utilized to identify and manipulate wetland areas for our simulations. The FUTURES model runs simulations based on the interactions between three sub-models: POTENTIAL, DEMAND, and Patch-Growing Algorithm (PGA) (Figure 3). The POTENTIAL sub-model combines LULC with socio-economic and physical environmental factors, including both natural and infrastructure features, to determine the possibility of development in an area. The DEMAND sub-model combines population change trends with LULC to determine the likelihood of development in an area. The PGA is a stochastic algorithm that combines the possibility of development from the POTENTIAL sub-model and the likelihood of development from the DEMAND sub-model to determine where development is likely to occur (Meentemeyer et al., 2013). We used the compiled database containing predictors derived from the input datasets to run the FUTURES submodels (Figure 2; Table 1). Each submodel has intermediate steps that contribute to the overall modeling process, ultimately leading to future predictions provided by the PGA submodel.

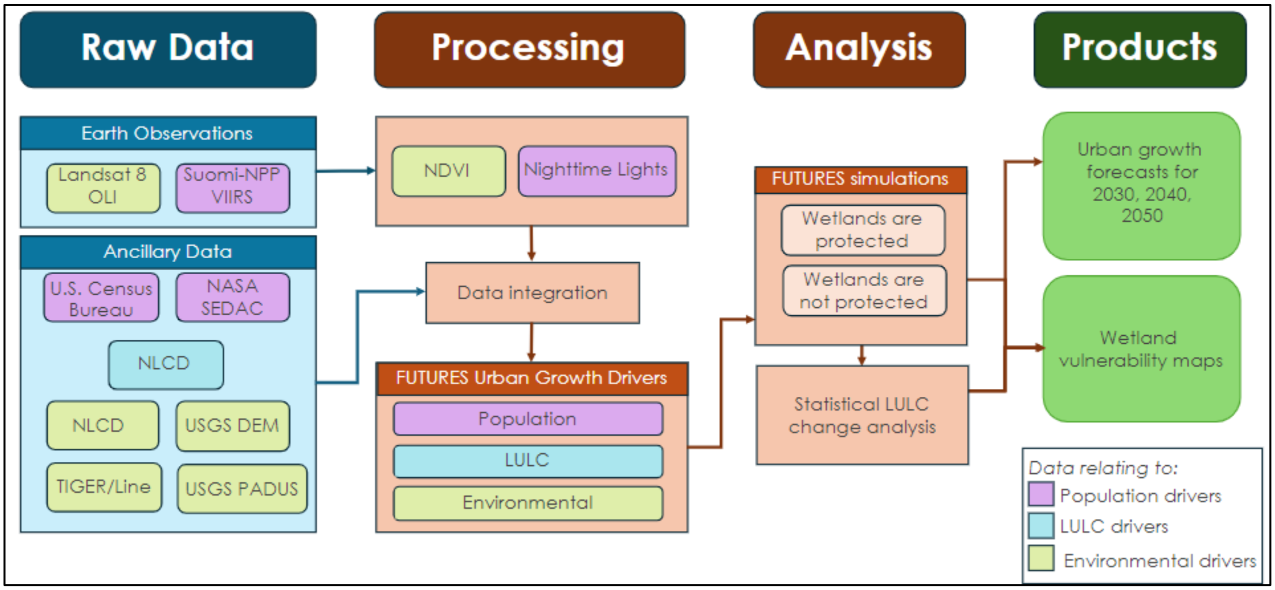

Figure 2. FUTURES flow chart.

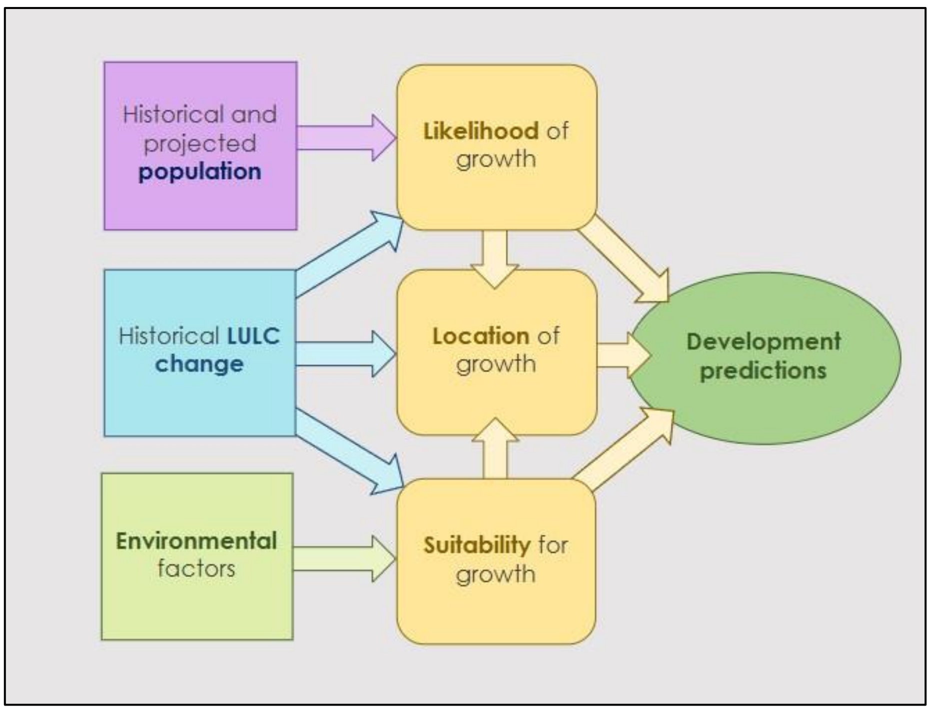

Figure 3. The interaction between FUTURES submodels for simulating predictions: POTENTIAL (likelihood of growth), DEMAND (location of growth), and PGA (suitability for growth).

The simulations produced six raster maps, three for each scenario, representing the years of interest (2030, 2040, 2050). Each map depicted a forecast of urban growth trends in the PRB for its respective year and scenario. Together, these forecasts enabled us to analyze the PRB's potential future development patterns and their impact on wetlands.

3.3.2 Statistical Analyses

After obtaining our urban growth projections for the two scenarios, we calculated the area of land classified as urban and the area of land classified as wetland for 2021, 2030, 2040, and 2050. We also calculated the percentage of land classified as urban and the percentage of land classified as wetland for 2021, 2030, 2040, and 2050 (Table B1; Table C1). We performed these calculations within each of the 81 counties in the study area. Using these percentages, we then assessed the percent change of urban and wetland areas within the entire basin. Finally, we created summary statistics to analyze the total, average, minimum, and maximum LULC changes. These analyses allowed us to evaluate the statistical change in the LULC classes between the decadal time steps for each scenario, which we used to determine basin-wide wetland vulnerability as well as counties with the higher amounts of projected wetland area loss.

4. Results & Discussion

4.1 Analysis of Urban Growth Projections

After generating the final maps, we compared the results for each scenario (Figure A1 and Figure A2). Our findings indicate that, under both scenarios, approximately 5% of non-urban areas are projected to be converted to urban areas by 2030, 8% by 2040, and 11% by 2050 (Figure 4). However, in scenario 1, no urban growth is projected to occur within wetland areas, while in scenario 2, there is a noticeable encroachment of urban development into wetland regions. When analyzing growth by county or city, rather than the entire basin, a different pattern emerges (Table B1). The average percentage change in urban growth across all counties by 2050 is projected to be 7%, with Banner County, Nebraska, experiencing the maximum projected change of 31.45%.

The total area of land conversion projected by 2050 is approximately 1,270 km², with Larimer County, Colorado, expected to undergo the largest conversion, developing into over 109 km² of urban area. In contrast, the average area change across all counties is about 14 km². Notably, 23 out of 81 counties within PRB are not projected to experience any urban growth at all. This is likely due to historical and projected population decreases combined with relatively minor historical urban growth from 2001 to 2021, resulting in a low likelihood of urban growth within these counties.

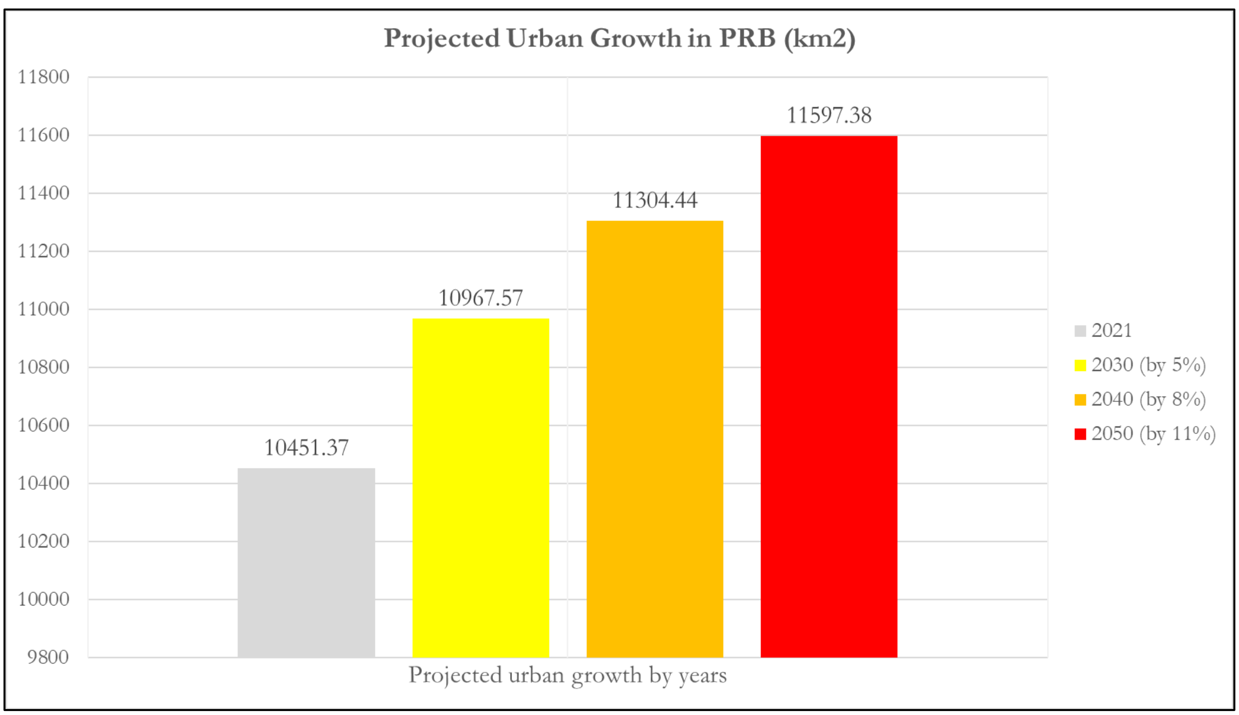

Figure 4. Projected Urban Growth in the Platte River Basin

It is important to highlight in the example of Lincoln, Nebraska in Lancaster County that most urban growth is projected to occur by 2030, with a 7% increase (represented in yellow on the map), followed by an additional 5.33% in 2040 (represented in orange), and 5.06% by 2050 (represented in red), totaling 17.38% growth in 25 years (Figure 5). Many other counties projected to grow show a similar trend, with significant urban growth anticipated by 2030. For example, Larimer County, Colorado is projected to grow by more than 12% (49 km²) by 2030, followed by 8% (33 km²) by 2040, and an additional 7% (28 km²) by 2050. These findings underscore the urgency of implementing wetland restoration and protection strategies across multiple regions.

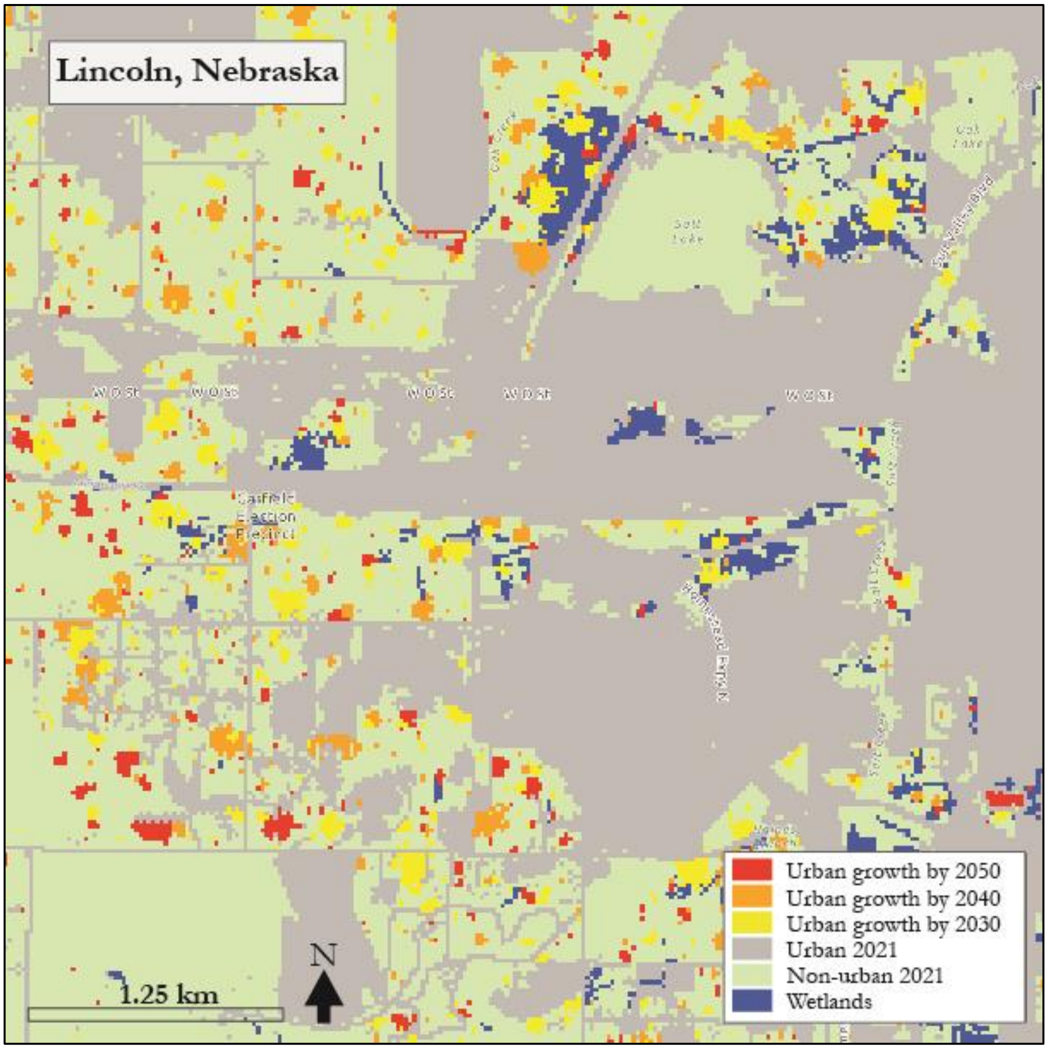

Figure 5. Urban growth projection on the case of fragment of Lincoln, Nebraska. Service Layer Credits: Nebraska Game & Parks Commission, Esri, TomTom, Garmin, FAO, NOAA, USGS, EPA, NPS, USFWS

4.2 Analysis of Wetland Vulnerability

Our findings regarding wetland vulnerability indicate that, under Scenario 1, no wetlands will be lost by 2050. However, in Scenario 2, 43.22 km² (about half the area of Manhattan) of the total 7,423.55 km² of wetlands would be lost to urban encroachment, representing 0.58% of the wetland area (Figure 6). Although a 0.58% loss of wetland area across the entire basin might seem insignificant, even this small percentage can have serious consequences for critical bird habitats, leading to fragmentation and disruption of habitat connectivity. Also, we see from our results that some counties would experience significantly higher percentages of wetland loss, further intensifying these impacts.

For instance, Broomfield County, Colorado is projected to lose 52.44% of its wetlands by 2050, while Denver County, Colorado is projected to lose 49.36%. To further summarize these findings, by 2050, 33 counties are expected to lose less than 1% of their wetlands, 13 counties will lose between 1% and 5%, and 5 counties will lose up to 13% (Table C1). The two Colorado counties mentioned above will experience the most substantial losses—nearly 50% or more. On the contrary, as mentioned previously, at least 23 counties are not projected to experience any urban growth by 2050, presenting the area of least concern regarding wetland vulnerability.

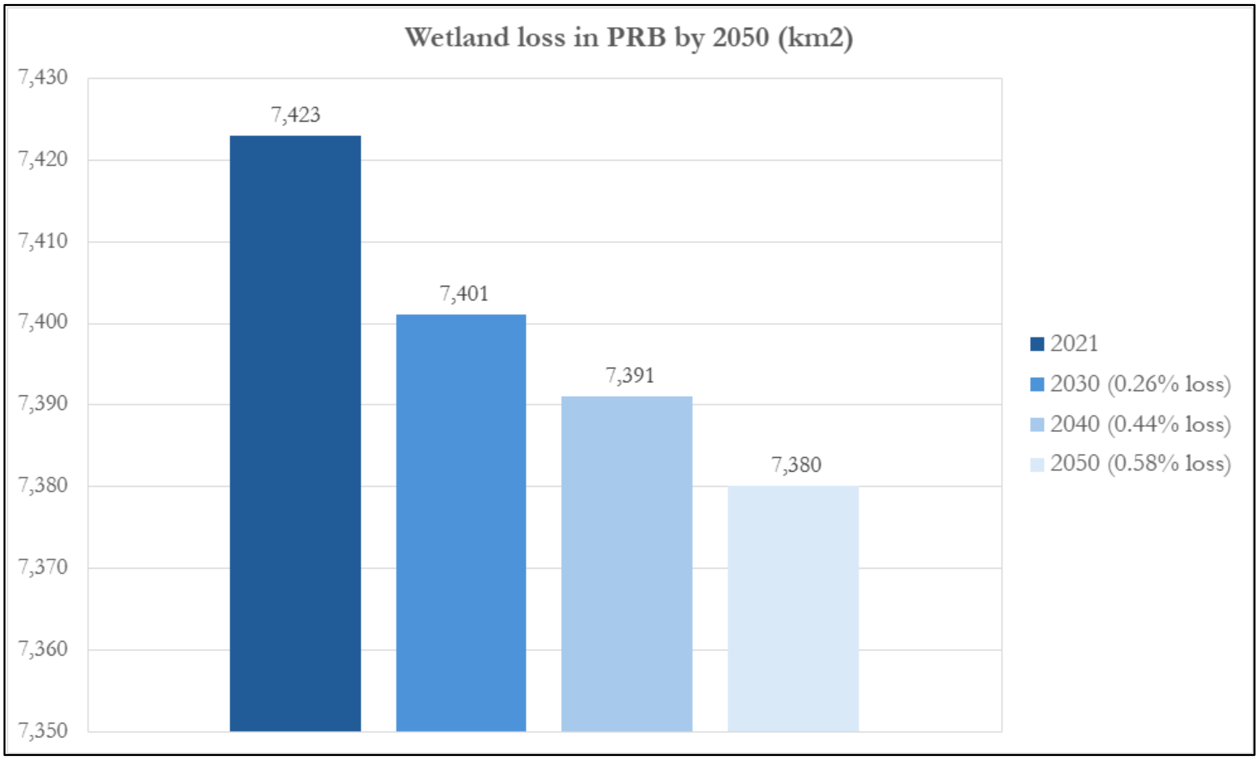

Figure 6. Predicted wetland loss in the Platte River Basin.

4.3 Errors & Uncertainties

In our project, several uncertainties were identified that require consideration. Our population estimates were captured and conducted at the county level, rather than on a finer scale such as census blocks. While county-level data provide a broad overview, using fine-scale data like census blocks would offer a more precise distribution of the population across the PRB. This could significantly enhance the accuracy of the urban growth model by reflecting more detailed spatial variation in population density and distribution.

Predicting urban growth is inherently uncertain due to factors like migration patterns, urban planning strategies, economic fluctuations, policy changes, and climate change impacts on wetlands. This unpredictable nature of urban growth will always have some degree of uncertainty regarding future developments. In addition to population changes, other agents such as agriculture, industry, and infrastructure development also influence land use and urban growth patterns. These factors could have differing demands for land use and potentially alter the trajectory of urban expansion. Including these variables in the model could provide a more holistic view of future land use changes and improve the robustness of the forecasts.

The FUTURES UGM offers a valuable feature for exploring different urban development patterns, including policies that encourage infill versus sprawl (Petrasova, 2016). In our project, we did not utilize the advantage of simulating these behaviors. Exploring a range of development patterns would provide a more comprehensive analysis of urban growth, highlighting the trade-offs between sprawl and infill development.

This could inform more effective urban planning strategies and policy decisions aimed at sustainable development.

4.3 Feasibility & Partner Implementation

Despite uncertainties, we found that NASA Earth observations, the FUTURES urban growth model, and our products are feasible for our partner to use in their wetland protection and restoration efforts. Earth observations from Suomi-NPP VIIRS and Landsat 8 OLI capture the large scale of the basin while being reliable and accessible. The FUTURES model is capable of processing large amounts of data over large scales while being free to use and open source. Our results show that these data and methods are feasible for our partner to implement into their consideration of where to focus their conservation efforts to protect the wetlands that are most vulnerable to urban encroachment. Our products depicting urban growth and wetland vulnerability in 13 priority cities are useful to AGP in deciding which cities they will focus on. Replicating this methodology by incorporating finer scales of population projection data, using more detailed wetland data such as the National Wetland Inventory or internal wetland datapoints, and producing additional scenarios of urban growth to envision various futures would additionally serve the partner's decision-making.

5. Conclusions

To conclude, while simulation and urban growth models inherently involve a degree of uncertainty stemming from their reliance on current and historical data to forecast future scenarios, the insights they provide remain invaluable. These models do not guarantee that present patterns and trends will persist unchanged, but they offer critical perspectives that are highly beneficial to decision makers, planners, and change agents, such as our partners, AGP. Despite their limitations, such studies are instrumental in understanding potential future developments, guiding decision-making processes, and informing long-term planning and conservation strategies. The value of these predictive tools lies in their ability to offer informed scenarios that help stakeholders anticipate and address potential challenges.

The FUTURES model, developed by the Center for Geospatial Analytics at North Carolina State University, was an especially fitting choice for this project. As an open-source program, it is accessible to anyone interested in using it with a wealth of step-by-step tutorials provided by the developers to facilitate learning and application. The model's flexibility and versatility make it particularly well-suited for simulating projections over large territories like the Platte River Basin. We were able to seamlessly integrate remotely sensed data along with other supplemental datasets to create a comprehensive dataset for this project. This adaptability is crucial for conducting thorough analyses over extensive areas, ensuring that the model can effectively support planning and conservation efforts on a broad scale.

Overall, this study offers significant value to our partners at AGP. Even if they do not run the simulations themselves, the ability to use the projections from the two scenarios and present these maps to the communities they aim to engage provides a compelling foundation for raising awareness. These visualizations can effectively communicate the urgency of enhancing conservation efforts in the Platte River Basin, helping to galvanize support and action.

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7. Glossary

AGP – Audubon Great Plains
DEM – Digital Elevation Model
DNB – Day/Night Band
Earth observations – Satellites and sensors that collect information about the Earth's physical, chemical, and biological systems over space and time
EPA – Environment Protection Agency
ETM+ – Enhanced Thematic Mapper Plus
FUTURES – Future Urban Regional Environmental Simulation
GEE – Google Earth Engine
NAIP – National Agriculture Imagery Program
NL – Nighttime Light
NLCD – National Land Cover Database
Non-stationary time-series data – parameters in the model with changing statistical properties in time-series analysis
OLI – Operational Land Imager
PRB – Platte River Basin
Stationary time-series data – parameters used in the model with constant statistical properties in time-series analysis
TM – Thematic Mapper
UGM – Urban Growth Model
USFWS – United States Fish and Wildlife Services
USGS – United States Geological Survey
VIIRS – Visible Infrared Imaging Radiometer Suite

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9. Appendices

Appendix A: *Maps with projected urban growth in Platte River Basin*

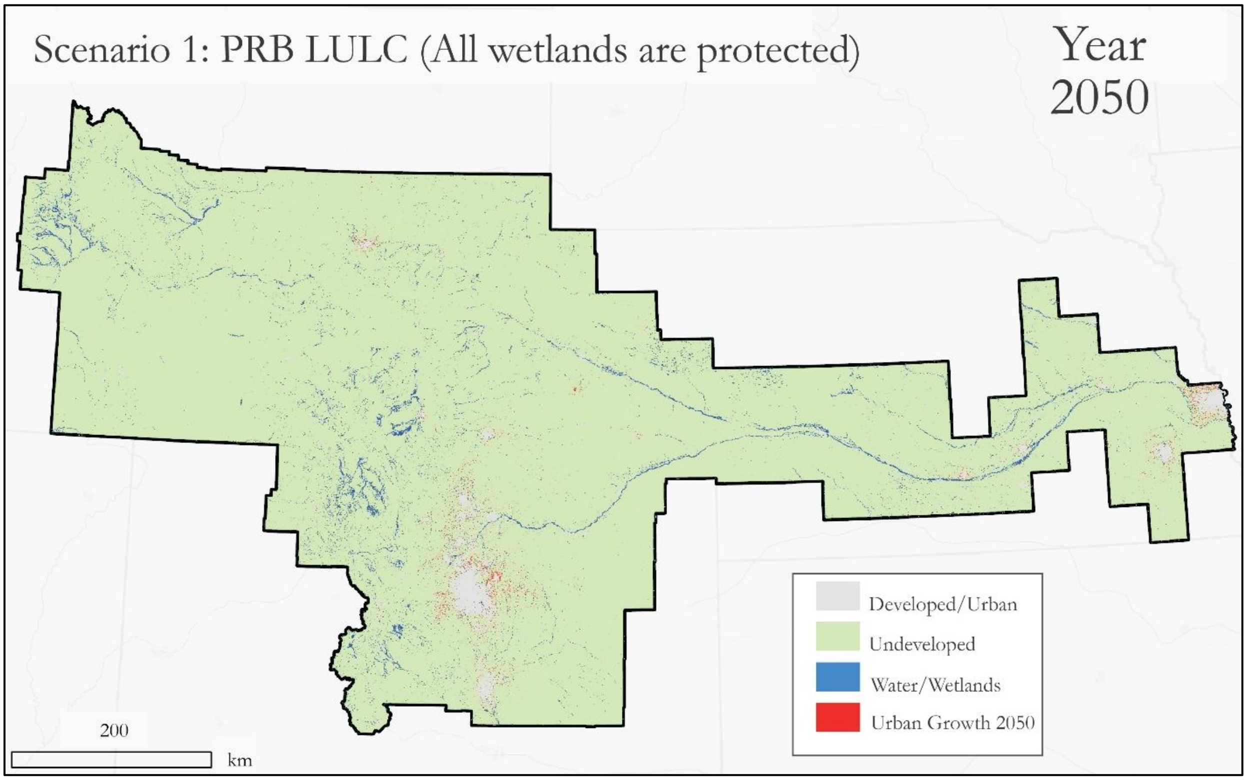

Figure A1. Forecasted PRB map for 2050 per Scenario 1 (all wetlands are protected)

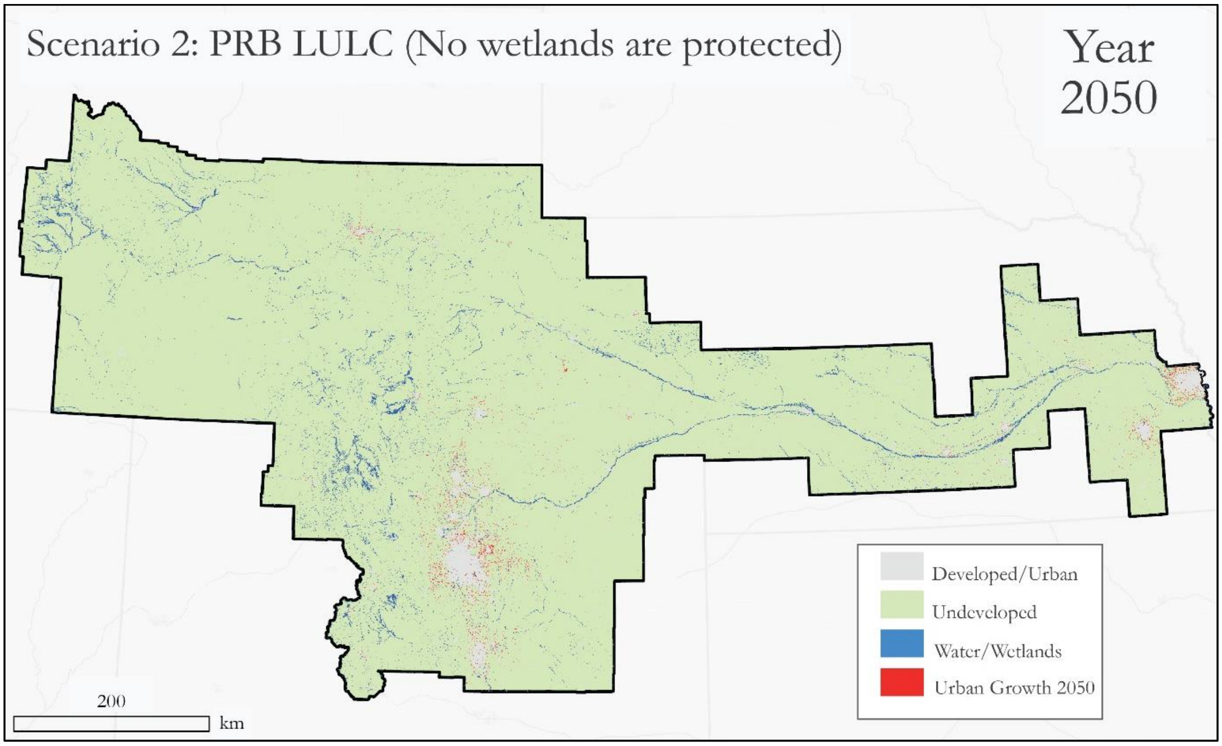

Figure A2. Forecasted PRB map for 2050 per scenario 2 (no wetlands are protected)

Appendix B: *Summary Table of projected urban growth within Platte River Basin for both scenarios.*

Table B1

*Summary of projected urban growth in PRB per county for each decade of interest (*STATEFP 8 = Colorado, STATEFP 31 = Nebraska, STATEFP 56 = Wyoming; LULC unit = km²)*

State FP	County Name	Urban Areas 2021	Urban Areas 2030	Urban Areas 2040	Urban Areas 2050	Urban Growth 2030 %	Urban Growth 2040 %	Urban Growth 2050 %
8	Broomfield County	54.9	61.6	66.3	70.1	12.33	20.91	27.76
8	Larimer County	399.6	448.8	481.5	509.5	12.32	20.50	27.51
8	Adams County	423.8	469.4	499.0	523.6	10.77	17.75	23.56
8	Boulder County	250.5	274.1	288.5	300.9	9.44	15.17	20.10
8	Jefferson County	438.8	479.0	502.2	520.8	9.16	14.46	18.68
8	Weld County	519.2	553.9	584.8	610.1	6.68	12.65	17.51
8	Douglas County	328.3	353.8	371.2	384.4	7.75	13.07	17.09
8	Arapahoe County	411.4	441.3	459.2	474.0	7.27	11.62	15.23
8	El Paso County	609.0	642.1	670.1	692.7	5.45	10.04	13.75
8	Gilpin County	19.2	20.7	21.3	21.8	7.87	11.16	13.53
8	Chaffee County	56.1	59.4	61.7	63.6	5.80	9.95	13.44
8	Lake County	15.6	16.8	17.2	17.5	7.83	10.60	12.41
8	Denver County	320.4	339.3	350.1	359.4	5.89	9.28	12.18
8	Routt County	67.0	70.8	72.7	74.3	5.73	8.58	10.91
8	Summit County	77.5	81.1	83.1	84.7	4.64	7.29	9.38
8	Elbert County	152.3	155.7	157.6	158.8	2.25	3.50	4.26
8	Clear Creek County	26.1	26.9	27.0	27.0	2.84	3.18	3.19
8	Sedgwick County	44.1	44.2	44.4	44.9	0.07	0.51	1.71
8	Park County	81.8	82.3	82.3	82.3	0.63	0.64	0.64
8	Washington County	152.8	153.6	153.6	153.6	0.52	0.52	0.52
8	Lincoln County	117.2	117.3	117.5	117.5	0.11	0.26	0.26

8	Jackson County	23.5	23.5	23.6	23.6	-	0.06	0.06
8	Grand County	75.1	75.1	75.1	75.1	-	-	0.03
8	Teller County	58.3	58.3	58.3	58.3	0.01	0.02	0.03
8	Morgan County	105.8	105.8	105.8	105.8	-	-	-
8	Logan County	146.8	146.8	146.8	146.8	-	-	-
31	Banner County	49.2	57.5	61.4	64.7	16.84	24.63	31.45
31	Sarpy County	185.5	205.3	219.5	231.6	10.67	18.30	24.86
31	Lancaster County	324.4	347.1	364.3	380.7	6.99	12.32	17.38
31	Douglas County	442.7	470.9	492.4	511.5	6.37	11.21	15.52
31	Buffalo County	153.0	162.3	168.8	175.0	6.13	10.38	14.40
31	Hall County	132.4	138.9	143.6	148.3	4.93	8.51	12.04
31	Platte County	108.8	110.6	114.8	120.1	1.60	5.48	10.40
31	Saline County	77.7	79.9	81.6	83.8	2.91	5.06	7.87
31	Deuel County	39.6	40.4	41.3	42.5	2.23	4.49	7.45
31	Cheyenne County	106.9	111.8	113.3	114.8	4.50	5.99	7.32
31	Box Butte County	74.4	76.7	77.6	78.8	3.13	4.34	5.90
31	Morrill County	63.0	64.4	65.0	66.3	2.20	3.11	5.14
31	Adams County	96.9	101.0	101.1	101.1	4.27	4.35	4.35
31	Sioux County	35.9	37.4	37.4	37.4	4.19	4.19	4.19
31	Kearney County	59.8	60.6	61.3	62.2	1.36	2.53	3.98
31	Colfax County	55.0	55.6	56.2	56.9	1.02	2.09	3.46
31	Phelps County	68.5	69.6	70.0	70.3	1.60	2.09	2.54
31	Gosper County	40.1	40.6	40.7	41.0	1.14	1.35	2.28
31	Howard County	59.8	60.4	60.8	61.1	1.11	1.77	2.20
31	Dodge County	100.8	101.0	101.1	102.0	0.18	0.32	1.22

31	Hamilton County	71.6	71.8	72.0	72.0	0.21	0.50	0.57
31	Seward County	78.8	79.0	79.2	79.2	0.23	0.44	0.47
31	Nance County	41.3	41.4	41.4	41.4	0.39	0.39	0.39
31	Polk County	50.4	50.4	50.4	50.5	-	-	0.26
31	Arthur County	10.8	10.8	10.8	10.8	-	0.06	0.22
31	Cass County	90.3	90.5	90.5	90.5	0.18	0.18	0.18
31	Logan County	16.2	16.2	16.2	16.2	-	-	0.01
31	Madison County	100.2	100.2	100.2	100.2	-	0.00	0.00
31	Scotts Bluff County	115.7	115.7	115.7	115.7	0.00	0.00	0.00
31	Saunders County	105.2	105.2	105.2	105.2	-	-	0.00
31	Keith County	73.2	73.2	73.2	73.2	-	-	-
31	Kimball County	63.5	63.5	63.5	63.5	-	-	-
31	Custer County	156.5	156.5	156.5	156.5	-	-	-
31	Boone County	68.0	68.0	68.0	68.0	-	-	-
31	McPherson County	10.3	10.3	10.3	10.3	-	-	-
31	Gage County	116.7	116.7	116.7	116.7	-	-	-
31	Dawson County	123.3	123.3	123.3	123.3	-	-	-
31	Antelope County	92.4	92.4	92.4	92.4	-	-	-
31	Lincoln County	171.4	171.4	171.4	171.4	-	-	-
31	Merrick County	64.8	64.8	64.8	64.8	-	-	-
31	Garden County	50.8	50.8	50.8	50.8	-	0.00	0.00
31	Frontier County	67.4	67.4	67.4	67.4	-	0.00	0.00
31	Perkins County	76.5	76.5	76.5	76.5	-	0.00	0.00
31	Butler County	72.9	72.9	72.9	72.9	-	0.00	0.00
56	Converse County	75.8	87.8	93.5	99.0	15.82	23.31	30.61
56	Natrona County	170.2	195.3	208.1	219.8	14.72	22.25	29.13

56	Laramie County	212.6	230.9	242.7	253.3	8.60	14.14	19.12
56	Albany County	85.5	92.9	97.1	101.2	8.63	13.47	18.33
56	Niobrara County	32.5	33.3	33.9	34.9	2.40	4.33	7.15
56	Goshen County	88.4	91.1	91.9	92.9	3.10	3.98	5.15
56	Platte County	66.9	68.8	69.3	69.8	2.80	3.49	4.27
56	Sublette County	81.7	83.0	83.0	83.0	1.60	1.60	1.60
56	Sweetwater County	174.3	176.2	176.7	177.1	1.04	1.34	1.59
56	Carbon County	142.3	142.3	142.3	142.3	0.03	0.03	0.03
56	Fremont County	183.5	183.5	183.5	183.5	0.00	0.00	0.00

Appendix C: *Summary of wetland area loss per county for 2030, 2040, 2050 per scenario 2*

Table C1
Wetland loss per county
*STATEFP: 8 = Colorado, 31 = Nebraska, 56 = Wyoming; Area unit = hectare (1 Ha = 0.01 km^2)

STATEFP*	County Name	Wetland area 2021	Wetland Area loss 2030	Wetland Area loss 2040	Wetland Area loss 2050	% Wetland Area Loss 2030	% Wetland Area Loss 2040	% Wetland Area Loss 2050
8	Adams County	3419.1	140.3	4.1	232.3	6.79	288.13	8.43
8	Arapahoe County	3515.7	143.9	4.1	236.2	6.72	304.35	8.66
8	Boulder County	6426.4	168.0	2.6	263.3	4.10	341.47	5.31
8	Broomfield County	137.3	28.5	20.8	50.7	36.90	71.99	52.44
8	Chaffee County	6791.6	26.8	0.4	45.2	0.67	59.13	0.87
8	Clear Creek County	2444.0	1.4	0.1	1.4	0.06	1.44	0.06
8	Denver County	299.9	76.6	25.5	116.8	38.94	148.03	49.36
8	Douglas County	4666.1	85.0	1.8	149.9	3.21	185.10	3.97
8	El Paso County	6851.7	105.2	1.5	204.7	2.99	269.10	3.93
8	Elbert County	6192.2	10.9	0.2	16.2	0.26	18.85	0.30
8	Gilpin County	656.8	4.1	0.6	6.6	1.00	7.82	1.19
8	Grand County	23712.8	-	-	-	-	-	-
8	Jackson County	50952.5	-	-	0.6	-	0.63	-
8	Jefferson County	3178.4	170.6	5.4	260.6	8.20	333.10	10.50
8	Lake County	7456.9	4.3	0.1	5.0	0.07	5.22	0.07
8	Larimer County	18232.0	195.8	1.1	326.2	1.79	443.72	2.43
8	Lincoln County	3619.1	0.1	-	0.1	-	0.09	-
8	Logan County	10645.0	-	-	-	-	-	-
8	Morgan County	6947.1	0.1	-	0.1	-	0.06	-
8	Park County	28960.5	2.0	0.0	2.0	0.01	1.98	0.01
8	Routt County	16536.1	15.5	0.1	28.7	0.17	41.85	0.25
8	Sedgwick County	3939.1	0.7	0.0	1.9	0.05	4.23	0.11
8	Summit County	5804.7	28.1	0.5	47.8	0.82	66.87	1.15

8	Teller County	3541.6	-	-	-	-	-	-
8	Washington County	1269.6	0.3	0.0	0.3	0.02	0.27	0.02
8	Weld County	14328.6	118.0	0.8	198.5	1.39	283.52	1.98
31	Adams County	1303.3	7.6	0.6	7.6	0.59	7.66	0.59
31	Antelope County	5766.1	-	-	-	-	-	-
31	Arthur County	5190.6	-	-	-	-	-	-
31	Banner County	320.6	0.8	0.3	0.8	0.25	1.17	0.36
31	Boone County	3023.9	-	-	-	-	-	-
31	Box Butte County	2071.4	2.5	0.1	2.8	0.13	2.79	0.13
31	Buffalo County	12151.7	71.4	0.6	129.4	1.06	179.08	1.47
31	Butler County	1392.0	-	-	-	-	-	-
31	Cass County	1932.2	0.4	0.0	0.5	0.02	0.45	0.02
31	Cheyenne County	707.0	5.2	0.7	7.4	1.04	8.01	1.13
31	Colfax County	1741.2	0.3	0.0	0.4	0.03	2.52	0.14
31	Custer County	7975.9	-	-	-	-	-	-
31	Dawson County	10606.8	-	-	-	-	-	-
31	Deuel County	1159.1	8.9	0.8	14.6	1.26	26.82	2.31
31	Dodge County	4376.1	0.9	0.0	4.0	0.09	6.48	0.15
31	Douglas County	2426.4	130.8	5.4	223.9	9.23	303.86	12.52
31	Frontier County	3422.6	-	-	-	-	-	-
31	Gage County	339.0	-	-	-	-	-	-
31	Garden County	16484.6	-	-	-	-	-	-
31	Gosper County	3301.2	2.6	0.1	2.6	0.08	2.97	0.09
31	Hall County	9173.7	42.4	0.5	84.2	0.92	118.61	1.29
31	Hamilton County	2450.3	0.1	-	0.1	-	0.09	-
31	Howard County	5342.6	5.7	0.1	8.9	0.17	11.61	0.22
31	Kearney County	1822.8	0.9	0.1	2.7	0.15	2.90	0.16
31	Keith County	9557.3	-	-	-	-	-	-
31	Kimball County	699.5	-	-	-	-	-	-
31	Lancaster County	1892.3	39.4	2.1	56.2	2.97	68.76	3.63

31	Lincoln County	21186.3	-	-	-	-	-	-
31	Logan County	5753.0	-	-	-	-	-	-
31	Madison County	2381.5	-	-	-	-	-	-
31	McPherson County	2737.4	-	-	-	-	-	-
31	Merrick County	10172.8	0.0	-	0.0	-	0.00	-
31	Morrill County	13624.1	15.3	0.1	19.5	0.14	30.24	0.22
31	Nance County	6704.1	3.2	0.1	3.2	0.05	3.24	0.05
31	Perkins County	360.3	-	-	-	-	-	-
31	Phelps County	2988.8	7.4	0.3	7.8	0.26	9.63	0.32
31	Platte County	4681.4	6.1	0.1	17.1	0.36	35.68	0.76
31	Polk County	1839.3	-	-	0.0	-	0.68	0.04
31	Saline County	403.8	0.4	0.1	1.0	0.25	1.89	0.47
31	Sarpy County	2556.3	88.7	3.5	137.9	5.39	188.87	7.39
31	Saunders County	2615.3	0.0	-	0.1	-	0.11	-
31	Scotts Bluff County	6163.9	-	-	-	-	-	-
31	Seward County	832.2	0.1	0.0	0.2	0.02	0.18	0.02
31	Sioux County	3097.0	2.1	0.1	2.1	0.07	2.07	0.07
56	Albany County	46434.2	49.8	0.1	75.3	0.16	95.40	0.21
56	Carbon County	44354.3	0.2	-	0.2	-	0.36	-
56	Converse County	13993.3	16.6	0.1	26.2	0.19	37.35	0.27
56	Fremont County	53162.6	-	-	-	-	-	-
56	Goshen County	7938.9	11.1	0.1	15.1	0.19	18.99	0.24
56	Laramie County	9632.5	26.3	0.3	43.3	0.45	62.37	0.65
56	Natrona County	13980.7	92.3	0.7	138.7	0.99	173.88	1.24
56	Niobrara County	8297.7	1.5	0.0	3.5	0.04	5.13	0.06
56	Platte County	14417.5	15.7	0.1	17.6	0.12	21.87	0.15
56	Sublette County	71583.5	8.7	0.0	8.7	0.01	8.73	0.01
56	Sweetwater County	13307.9	2.3	0.0	3.8	0.03	4.23	0.03