Evaluating the Effects of Future Land use/Land cover and Agricultural Conservation Practices Scenarios on Streamflow and Water Quality in the Maumee River Watershed

by

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Abstract

Lake Erie's water environment has been a growing concern due to its severe water eutrophication problems which primarily caused by the accumulation of nutrients, particularly phosphorus, from both point and nonpoint source pollutants originating from the Maumee River Watershed (MRW). Despite global studies on the watershed's nutrient dynamics, the complex interactions between land use and land cover (LULC), agricultural conservation practices (ACPs), and their effects on the water environment remain inadequately understood within the MRW. In our study, we designed seven future scenarios involving LULC and ACPs to explore their impacts on the MRW. We employed the Land Change Modeler (LCM) and SWAT+ (Soil and Water Assessment Tool_Plus) to simulate future scenarios of LULC changes and to model the hydrological conditions of the watershed from 2046 to 2065, respectively. ACPs were set up in SWAT+, and we also incorporated meteorological data under the RCP8.5 scenario as future climatic conditions. We selected four hydrological parameters—streamflow (Q), Total Suspended Solids (TSS), Soluble Reactive Phosphorus (SRP), and Total Phosphorus (TP)—to analyze the impacts of various LULC and ACP scenarios on MRW. Our research found that ACP scenarios have a more significant impact on MRW's streamflow and water quality, but the effects of LULC changes are also non-negligible. We further analyzed the impacts of different LULC scenarios on the MRW's water environment in greater depth, both temporally and spatially, and found that different LULCs have more pronounced effects at the spatial scale. Although different LULC scenarios can mitigate impacts to varying degrees in different areas, our study also identified that the most significant LULC types on the water environment are open spaces and agricultural lands. Therefore, we suggest that the ideal future development model for MRW should involve managing open spaces reasonably and reducing fertilizer input in agricultural lands, while moderately increasing the proportion of open spaces and medium to high-intensity urban land in urbanized areas and reducing the area of agricultural land in the watershed. This model would effectively improve MRW's streamflow and water quality while accommodating agricultural, economic, and population growth needs.

Table of Content

Chapter 1: Introduction

The water environment issues caused by high nutrient loading and streamflow have brought serious ecological and human health problems to Lake Erie, one of the Great Lakes in the U.S. Among the most critical are the harmful algae blooms (HABs), primarily sourced from phosphorus (P) and sediment loading (Liu et al., 2019; Xu et al., 2018; Scavia et al., 2023; Michalak et al., 2013; Motew et al., 2019; Olaoye et al., 2021). Numerous studies indicate that the Maumee River Watershed (MRW), with over 70% agricultural land use, is the primary contributor to Lake Erie's nutrient loadings (Kast et al., 2021; Maccoux et al., 2016; Cousino et al., 2015). These agricultural lands, acting as nonpoint source pollution, contribute significantly to the watershed's Total Phosphorus(TP), Soluble Reactive Phosphorus (SRP) and Total Suspended Solids (TSS), ultimately leading to HABs. Agricultural Conservation Practices (ACPs) have been continuously studied in this watershed as crucial mechanisms for reducing nonpoint source nutrient and sediment transport, highlighting their potential for mitigating HABs (Michalak et al., 2013; Bosch et al., 2013). Relevant research indicates that ACPs, including No Tillage, Conventional Tillage, Tile Drainage, Cover Crops, and Nutrient Management, can effectively reduce levels of SRP, TP and TSS (Kalcic et al., 2016; Kast et al., 2021; Daloglu et al., 2012; Rittenburg et al., 2015). However, research also indicates that some common practices, like Buffer Strips and Grassed Waterways, may have minimal effects on reducing nutrient levels (Smith et al., 2015; Dodd and Sharpley, 2016). Nevertheless, these conclusions can vary due to the precision and variability of model input data. Furthermore, research demonstrates that certain subbasins within the MRW exhibit significant concentrations of urbanization, and future rational urban planning could mitigate water environmental issues to some extent.

Land use and land cover (LULC) changes are among the significant factors that directly impact hydrological processes, water environments, and socio-economic activities (Malede et al., 2022; Peraza-Castro et al., 2018). These changes, often driven by human activities such as population growth and changes in production and living patterns, manifest in forms such as urban expansion, degradation of agriculture and pasture, and industrialization, which in turn affect the water environment (Malede et al., 2022; Wang and Kalin, 2018). Studies have shown that these impacts are mostly negative. For example, rapid urbanization can lead to increased surface runoff and evapotranspiration due to the increase in impervious surfaces, while the expansion of agricultural and pasture lands can accelerate the enrichment of water bodies with nutrients through the input of more fertilizers, pesticides, and other chemical components, with P being the most significant (Gong et al., 2019; Fan and Shibata, 2015). However, research also indicates that the impact of LULC on the water environment is spatially and temporally heterogeneous. For instance, regions with similar land type compositions may have different impacts on the water environment due to their locations within a watershed and differences in human activities (de Mello et al., 2018; Wilson, 2015). Moreover, the distance between different LULC types and water bodies can also affect nutrient inputs into water quality (Huang et al., 2019). On the temporal scale, LULC is subject to the influences of natural processes and human behaviors, adding greater uncertainty to water issues (Serpa et al., 2017; Sharannya et al., 2021). Despite the MRW being predominantly an agricultural watershed, it also contains many high-intensity urban areas, including Perrysburg, Defiance, Fort Wayne, and large areas of pasture in the northwest. However, the impact of these LULC types on surface runoff and nutrient loadings, particularly P, has historically been understudied. Therefore, in this study, we innovatively explore the spatial and temporal variations of these less-studied LULC types on watershed streamflow and P loading at the scale of Landscape Units (LSU), where LSU is a refined classification unit in the SWAT+ (Soil and Water Assessment Tool Plus), considered as a collection of multiple Hydrological Response Units (HRUs) (Chawanda et al., 2020).

In contrast to the research focused on ACPs within the agricultural lands of MRW, other watershed studies have placed more emphasis on a broader range of LULC classifications, such as urban, forest, wetlands, and farmlands (Khoshnood Motlagh et al., 2021; Zhao et al., 2023). These studies primarily examine the impacts of LULC changes on the aquatic environment by comparing carefully designed LULC scenarios. Such scenarios are often created based on historical trends of LULC changes and regional development goals for the future. The fundamental findings suggest that reductions in forests, wetlands, and farmlands can beneficially reduce surface runoff and nutrient loadings in water to varying degrees, while increased urbanization tends to deteriorate water quality and increase surface runoff (Pandey et al., 2023; Ren et al., 2014; Carle et al., 2005). In terms of research methodologies, some studies utilize remote sensing satellite imagery to extract LULC information and employ algorithms to deduce LULC evolution, whereas a greater number of studies simulate spatial changes in complex systems using LULC models like Dyna-CLUE and Land Change Modeler (LCM) (Lin et al., 2021; Malede et al., 2022; Shrestha et al., 2018; Fan and Shibata, 2015). The LCM model was chosen for our study because of its greater dynamic predictive ability and spatial simulation accuracy compared to other models, particularly in urban growth and environmental protection areas. Past research has seldom analyzed the historical changes in MRW's LULC, including urban land, nor explored the impacts of various future LULC changes scenarios on the aquatic environment. Therefore, to address the gap in MRW research concerning a wider array of LULC types, we utilized LCM to analyze past LULC changes and designed several future LULC scenarios for 2046. These scenarios examined the effects of varying degrees of urbanization, agricultural, and pasture conservation on watershed streamflow and water quality improvement.

In addition to LULC changes, climate change has been confirmed as another key issue leading to water environment problems (Greenough et al., 2001; Moore et al., 2008). This is primarily due to climate change impacting the hydrological cycle through altering future precipitation spatial and temporal distributions, water temperature, evapotranspiration, and water stratification, etc (Yuan et al., 2020; Giorgi et al., 2019; Arnell, 2004; Kundzewicz et al., 2010). For instance, regarding HABs, higher water temperatures and increased precipitation can accelerate the concentration of water pollutants including nutrients, thus intensifying the production of HABs (Barruffa et al., 2021; Carstensen et al., 2023; Wells et al., 2020; Paerl et al., 2011). Research on the impact of climate change on the MRW mainly utilizes General Circulation Models (GCMs), the hydrological model SWAT, and statistical models related to HABs to analyze the effects of climate change on HABs, with GCMs widely used for predicting future climate and driving hydrological models (Cousino et al., 2015; Culbertson, 2016; Culbertson, A. M., 2015; Kalcic et al., 2019). These studies suggest that future climate may reduce nutrient loadings thus the scale of HABs, even though increased water temperature may mitigate this effect (Scavia et al., 2021). However, in MRW, few studies comprehensively consider and compare the impact of future climate, LULC, and ACPs on the water environment, even though such impacts, especially the combined and synergistic effects of climate change and LULC, have been demonstrated in other watersheds (Karlsson et al., 2016; Kundu et al., 2017; Rahman et al., 2015).

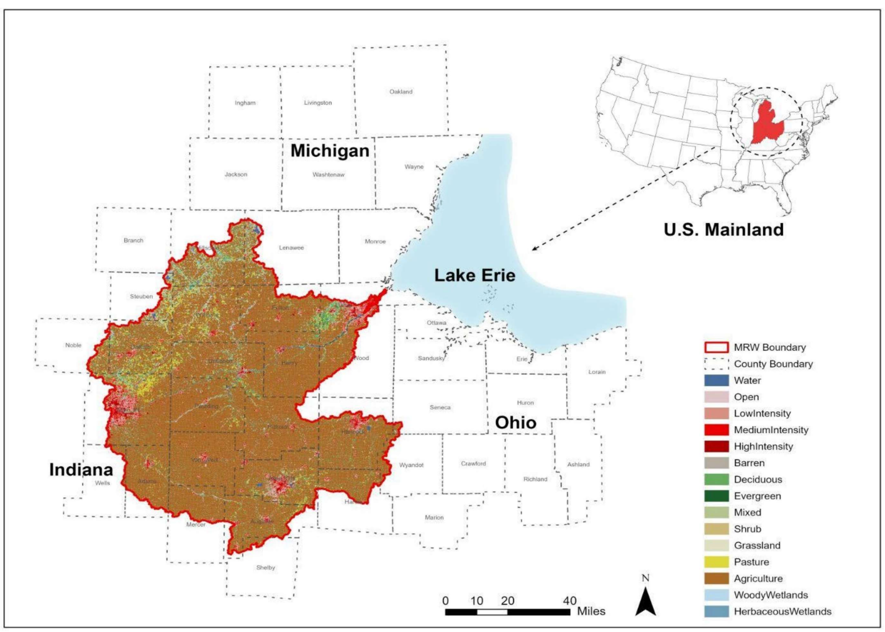
Considering the above research gaps, our research question is: In the future, what are the mitigation effects of LULC and ACPs scenarios on streamflow and water quality issues in the MRW? The main research objectives include: 1) to investigate the effects of future LULC and ACPs on the water environment of MRW separately; 2) to investigate the differences among various LSUs' hydrological performance under different LULC and ACP scenarios and which scenario performs better.

Chapter 2: Material and Method

2.1 Study Area

Our study area is the Maumee River Watershed, located in northwest Ohio (Figure 1). It spans Ohio, Indiana, and Michigan, extending from 40° 23′ to 42° 5′ N latitude, and between 83° 20′ and 85° 15′ W longitude (Verma et al., 2015). Originating near Fort Wayne, Indiana, it stretches over 130 miles to Lake Erie, covering a total area of approximately 6,330.1449 square miles, as measured at the USGS gauging station in Waterville, Ohio (Station #04193500) (Verma et al., 2015; Scavia et al., 2021). The MRW is the largest contributor of P to the western basin of Lake Erie, with about 88% of its TP loading coming from nonpoint sources, primarily agriculture (Kast et al., 2021; Maccoux et al., 2016).

The watershed is predominantly composed of agricultural lands, urban areas, pastures, and forests, with agricultural land making up more than 70% of the area, primarily rotating between soybeans, corn, and winter wheat. Urban areas, pastures, and forests account for approximately 11%, 6%, and 6% of the LULC, respectively (Yuan et al., 2020; Culbertson et al., 2016). The largest urban areas within the watershed are Toledo and Fort Wayne, with other urban areas scattered throughout the watershed. Pastures are mainly concentrated in the northwest part of the watershed. The overall terrain of the watershed is flat, and the soil type is mainly clay, with tile drainage commonly used in agriculture to address issues with natural drainage (Muenich et al., 2016; Cipoletti et al., 2019). To mitigate the high nutrient loadings from agriculture, since the 1990s, many farms have adopted ACPs to reduce nutrient loads in the watershed, including conservation tillage, vegetative buffer strips, nutrient management, and cover crops (Culbertson et al., 2016).



Maumee River Watershed

Figure 1. Study Area and Subregions: The map displays the location of Maumee River Watershed (MRW) and its location in relation to Lake Erie. MRW crosses Indiana, Ohio, Michigan, and the LULC map has a total of 15 LULC categories based on the National Land Cover Database (NLCD).

2.2 Study Framework

Our study primarily considers two change drivers—LULC changes and ACPs—and their impact on the water environment of the MRW (Figure 2). We have selected four indicators to represent MRW's streamflow and water quality: surface runoff for streamflow, and SRP, TSS, and TP for water quality. We utilize the LCM to simulate and predict future LULC change scenarios, while different LSUs are delineated using SWAT+. In SWAT+, we set up different ACP scenarios and input future climate data. Ultimately, by integrating both models, we aim to analyze and compare the effects of different future LULC scenarios and ACP scenarios on MRW's streamflow and water quality at the LSU scale.

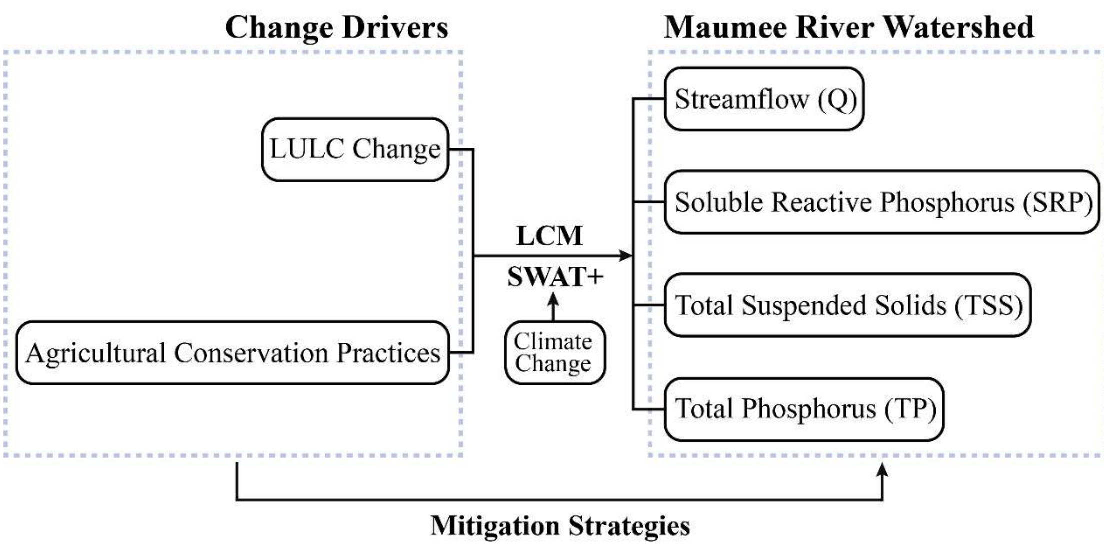


Figure 2. Study Framework: The diagram illustrates our overall research framework, focusing on the impact of two change drivers—LULC changes, ACPs—on streamflow (Q) and water quality indicators such as Total Suspended Solids (TSS), Soluble Reactive Phosphorus (SRP), and Total Phosphorus (TP) within the MRW. This framework is utilized to study the effects of various future LULC and ACP scenarios on MRW's streamflow and water quality.

2.3. LULC & Land Change Modeler

2.3.1 LULC Scenarios

We designed eight scenarios, including a baseline scenario, to explore effective measures that could mitigate water environmental issues. Among these, the S1-S5 are future LULC change scenarios (Table 1), primarily aimed at investigating future land planning and development strategies, set mainly in the LCM. The specific settings of the model are determined through a Markov matrix, which reflects the probability of one LULC type transitioning to another. We adjust these probabilities to achieve the desired scenario settings. Whereas our baseline scenario S0 keeps the LULC of 2016 unchanged to 2046 to enable comparisons with other scenarios.

Among the five LULC scenarios, the first is the Historical LULC Development scenario (S1), which maintains the LULC transition probabilities observed from 2011 to 2016 to predict LULC in 2046. S2 and S3 relate to urban development, with S2 serving as a Low Intensity Development scenario. It aims to reduce the future area of medium and high-intensity urban lands by limiting the transition from barren land, open space, and low intensity to medium and high intensity. In contrast, S3 encourages transitions from barren land, open space, and low intensity to medium and high intensity, thus increasing the future area of medium and high-intensity urban lands. S2 and S3 primarily explore the impact of urban development models of varying intensities on the MRW's water environment. Scenarios S4 and S5 are the Pasture Protection and Agriculture Protection scenarios, respectively. Given the existing proportion of pasture in the MRW, S4 aims to explore the mitigating effects on the water environment of future strategies that limit the transition of urban land types, including open, low, medium, and high intensity, to pasture. Similar in design strategy to S4, S5 aims to protect the agricultural land, which accounts for the highest LULC proportion in the MRW.

Table 1 Descriptions and Settings for Future LULC Scenarios

	Name	**Description**	**Setting**
S0	Baseline	Suppose the LULC of 2016 unchanged	Use the 2016 LULC map as the future map
S1	Historical LULC Development	Maintain the historic trend of LULC changes from 2011 to 2016 to predict the 2046 LULC	Maintain preliminary LULC transfer possibility
S2	Low Intensity Development	Encourage the development of Open Space & Low Intensity	Reduce the transition possibility from Barren, Open, Low to Medium, High by 50%
S3	Compacted Development	Encourage the development of Medium & High Intensity	Increase the transition possibility from Barren, Open, Low to Medium, High by 50%
S4	Pasture Protection	Limit the transition from Pasture to urban developed areas	Set the transition possibility from Pasture to Open, Low, Medium, High to 0%
S5	Agriculture Protection	Limit the transition from Agriculture to urban developed	Set the transition possibility from Agriculture to Open, Low, Medium,

		areas	High to 0%

2.3.2 Land Change Modeler Basics

The Land Change Modeler (LCM) developed by IDRISI Selva is a software designed to assess LULC changes and to predict future LULC scenarios accurately (Anand et al., 2018). Besides, it is extensively used for evaluating practical applications and measures related to LULC in the future as well (Mas et al., 2014; Remondi et al., 2016; Olmedo et al., 2015; Wilson and Weng, 2011). LCM employs the CA_Markov model integrated within IDRISI for LULC modeling, where CA (Cellular Automata) operates on a grid of cells, using rules based on the state of neighboring cells to infer changes over time in LULC for each cell. This approach is suitable for simulating more complex spatial processes (Gumindoga et al., 2014; Hand, 2005). The Markov chain models predict the likelihood of each LULC type transitioning to another by analyzing the process of change between two LULC maps, thereby estimating future LULC for a specific year (Anand et al., 2018; Zhao et al., 2023).

2.3.3 Land Change Modeler Setting

We conducted predictions of LULC at the county scale since SWAT+ operates with land classification at the subbasin or LSU level, a hydrological classification approach we believe is not applicable to the realm of urban planning. Therefore, we performed future LULC simulations and predictions for the more than thirty counties covering the total area of MRW, including scenarios of future LULC. Our LULC map inputs are derived from the National Land Cover Database (NLCD), selecting maps from the years 2011, 2016, and 2021. The 2011 and 2016 maps serve as input for the LCM, while the 2021 map is used for model validation (Table 2). The study area encompasses 15 LULC types as defined by the NLCD, which include Water, Open Space, Low Intensity, Medium Intensity, High Intensity, Barren Land, Deciduous Forest, Evergreen Forest, Mixed Forest, Shrub, Grassland, Pasture, Agriculture (Cultivated Crops), Woody Wetlands, and Emergent Herbaceous Wetlands. Additional model inputs include Basis Road Layers from OpenStreetMap (OSM) and Digital Elevation Models (DEM) from the USGS National Elevation Dataset (NED) at a 30m resolution.

In our research, we applied the Weighted Normalized Likelihood (WNL) method within LCM, which is particularly effective for modeling a large number of transitions simultaneously due to the diverse LULC types in our study area (Eastman et al., 2019). Although the Multi-Layer Perceptron (MLP) method is commonly used for its ability to model complex non-linear relationships, it was not adopted in our study due to its limitation of modeling a maximum of nine LULC transitions (Mishra et al., 2014; Mirici et al., 2018). The WNL method involves treating each LULC transition type as a sub-model for training, with our driving variables including evidence likelihood of LULC changes, distance from road, slope, and population density data (Table 2). The evidence likelihood of LULC changes is generated by LCM calculations, while distance from road and slope are processed using spatial analysis tools in ArcGIS Pro, and population density data are sourced from the Humanitarian Data Exchange (HDX).

Table 2 LCM Input Data and Driving Variables
(a) Three basic types of inputs for LCM and their data sources

Input Data	**Data Source**
LULC Maps	NLCD LULC map for the year 2011, 2016, 2021
Basis Road Layers	Open Street Map (OSM)
DEM	USGS NED (30m)

(b) Four driving variables used for training sub-models in LCM and their data sources.

Driving Variables	**Data Source**
Evidence Likelihood of LULC Change	Transition potential Map manipulated by LCM
Distance From Road	"Euclidean Distance" by ArcGIS
Slope	"Slope" by ArcGIS
Human Population	Humanitarian Data Exchange

2.3.4 LCM Validation

In addition to the accuracy reports after each model training inherent in the LCM, we employed Kappa Statistics for the validation of our model inputs and predictive capability. Kappa Statistics, based on the confusion matrix, measures the spatial consistency between predicted and actual LULC maps and is widely used in the validation process of LCM models (Tariq et al., 2022; Mehrabi et al., 2019). The confusion matrix is an effective method for measuring the accuracy of classified remote sensing images (Leta et al., 2021; Morales-Barquero et al., 2019). Typically, a Kappa Statistic value above 0.8 is considered indicative of good model predictive accuracy.

Under the same model settings, we predicted the 2021 LULC map based on the 2011 and 2016 LULC maps. Subsequently, we randomly selected 100,000 points on the predicted 2021 LULC and the actual 2021 LULC maps at identical locations. A confusion matrix was constructed using the LULC types represented by these 10,000 points to calculate the Kappa Statistics.

2.4 Agricultural Conservation Practices Scenarios

Besides the five LULC scenarios, the other two scenarios represent common and practical ACPs in the watershed, focusing on the effectiveness of adopting protective measures on agricultural land in the future (Table 3). S6 is the No Tillage Enforcement scenario, because no-tillage has been proven to be an effective agricultural measure in the MRW for significantly reducing nutrient loadings. Its mechanism of action mainly involves reducing soil disturbance to leave crop residue on the fields, substantially reducing nutrient content in soil sediment (Bosch et al., 2014; Smith et al., 2015; Yuan and Koropeckyj-Cox, 2022). Therefore, we converted 50% of fields from conventional tillage and 50% from reduced tillage to no-tillage to enhance the efficacy of no-tillage. The data and definitions for conventional tillage, reduced tillage, and no-tillage are based on the Operational Tillage Information System (OpTIS). Additionally, research indicates that farm fertilizer is the primary source of P contributing to Lake Erie, accounting for up to 75% (as of 2014 data) (Scavia et al., 2016). Thus, S7 aims to reduce nutrient input through a 50% reduction in P fertilizer application. By analyzing and comparing these two types of scenarios with another five LULC scenarios, our goal is to determine which approach may be more effective in mitigating water environmental issues in the future.

Table 3 Descriptions and Settings for Future ACPs Scenarios

	Name	**Description**	**Setting**
S6	No Tillage Enforcement	Low Soil Disturbance to leave crop residue on the fields to heavily reduce nutrient in soil sediment	Change 50% of Conventional Tillage & 50% Reduced Tillage Fields to No-Tillage

S7	P Fertilizer Reduction	Reduce nutrient input through fertilizer reduction	Reduce P fertilizer input rate by 50%

2.5 Future Climate

Our future climate settings are based on Version 4 of Community Climate System Model (CCSM4), which has been shown by related studies in the MRW to perform better compared to other climate models and is one of the most widely applied climate models (Kalcic et al., 2019; Yuan et al., 2020; Culbertson et al., 2016). We selected temperature (Tmax, Tmin) and precipitation (Prcp) data under the RCP8.5 scenario, while other climate data including solar radiation, relative humidity, and wind speed were generated in the SWAT+ weather generator. Among the four pathways used for climate modeling (the others being RCP2.6, RCP4.5, and RCP6.0), RCP8.5 can be understood as a high greenhouse gas emissions pathway, corresponding to higher temperatures and more significant climate change (Schwalm et al.; Riahi et al.). Since it does not include any specific climate mitigation targets, it can serve as a baseline scenario for future climate (Riahi et al.; Xin et al.). We selected climate data for a total of 12 stations under the RCP8.5 scenario for the years 2046-2065 as the climate data input for SWAT+ and applied it in the simulation of each future LULC and ACPs scenario.

2.6 SWAT+

SWAT+ is a time-continuous, semi-distributed hydrological model that represents a significant update to the SWAT model, which has been proven effective and comprehensive over the past twenty years (Bieger et al., 2017; Chawanda et al., 2020). Tests and existing studies indicate that its hydrological simulation results are comparable to SWAT and have greater flexibility in the spatial representation of interactions and processes within watersheds (Bieger et al., 2020; Wu et al., 2020). SWAT+ introduces the concept of LSUs, which are finer subdivisions on subbasins based on channel thresholds (Chawanda, 2020). LSUs can be further divided into Hydrologic Response Units (HRUs), similar to the classification in SWAT, referring to units within each subbasin with unique land use, soil, and slope characteristics. LSUs enable SWAT+ to better simulate landscape position, overland routing, and floodplain processes. Additionally, SWAT+'s advantages include more flexible adjustments of land use and management variables, more flexible settings of spatial interactions within the watershed, and rapid calibration, etc (Bieger et al., 2017; Wu et al., 2020; Kiprotich et al., 2021; Nkwasa et al., 2020).

Our lab has set up and calibrated the MRW's SWAT+ model. The R-squared values for Q, TSS, SRP, and TP are 0.89, 0.66, 0.72, and 0.81, respectively, indicating good calibration results.

Regarding the six future LULC scenarios (S0-S5), we merged the county-level 2046 LULC maps for each scenario and clipped them with the MRW boundaries to produce LULC maps of the watershed for different future scenarios. Subsequently, we re-inputted the new maps into SWAT+ and combined them with future climate data to simulate the hydrology of the MRW for the 2046-2065 period. The two ACPs scenarios are based on the LULC map of scenario S1, with the settings for agricultural practices completed in SWAT+. We compared the simulation results of these eight future scenarios and conducted hydrological analysis at the LSU scale.

Chapter 3: Results and Discussion

3.1 Historic LULC Changes

We initially utilized the LCM to analyze the LULC changes during the periods 2011-2016 and 2016-2021 (Figure 3). Our analysis focused on LULC categories relevant to our future LULC scenarios, including those related to urban development: open space, barren land, low intensity, medium intensity, and high intensity, as well as pasture and agriculture. From the first two diagrams showing the net change in LULC area, we observed an overall trend over the decade of decreasing open space, pasture, and agriculture, alongside increasing low intensity, medium intensity, and high intensity areas. This phenomenon indicates a continuous urbanization process within the MRW. However, it is noteworthy that when comparing the area changes and the magnitude of changes between the two periods, the rate of decrease in open space and pastureland has slowed, the rate of increase in low-intensity land has risen slightly, and the rate of growth in medium- and high-intensity urban land has slowed. This might suggest a deceleration in the urbanization rate of the MRW, or potentially a shift from medium and high-intensity development patterns towards a low-intensity development pattern. Furthermore, barren land experienced a reduction followed by an increase, but given the previous analysis, we consider this change insufficient to represent the urbanization process of the MRW. Moreover, its small base number might also likely be the reason for its highest growth rate during 2016-2021.

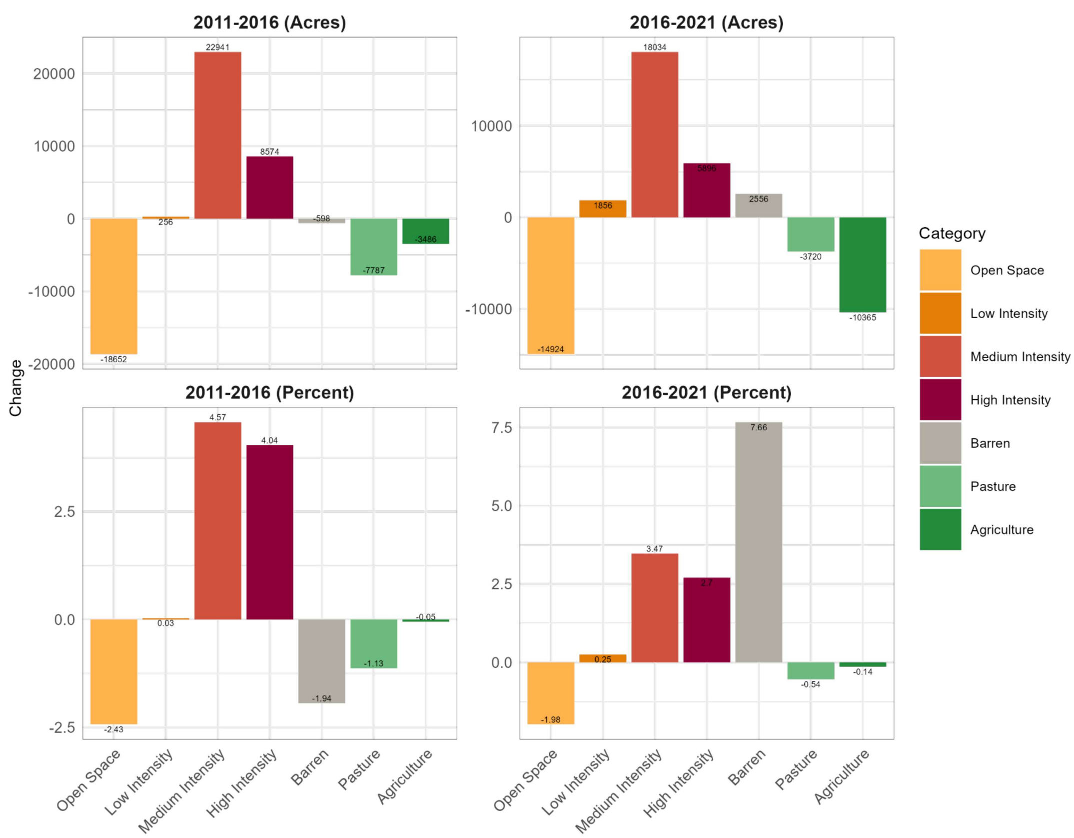


Figure 3. Net Change of LULC during 2011-2016 and 2016-2021: The diagram shows the net changes in LULC for two historical periods. Top left: Net change in LULC area from 2011 to 2016 (in acres); Top right: Net change in LULC area from 2016 to 2021 (in acres); Bottom left: Percentage of net change in LULC area from 2011 to 2016 (in %); Bottom right: Percentage of net change in LULC area from 2016 to 2021 (in %).

3.2 Land Change Modeler Validation

The confusion matrix displayed the distribution of values for each LULC classification in the predicted versus actual 2021 LULC map, based on a random selection of 100,000 points (Table 4). Overall, the model's predictions were relatively accurate, as evidenced by the values along the diagonal (excluding N/A) being in the top 10% (highlighted in pink), indicating the number of points with spatial consistency across the two LULC maps. Furthermore, the accuracy column on the far right revealed that nearly all LULC categories had an accuracy higher than 90%, with most even exceeding 95%. In terms of the total distribution of points across various LULC categories, it was evident that the MRW's 2021 LULC predominantly consisted of agricultural land, deciduous forests, various urban lands, and pasture (highlighted in orange), with other LULC categories covering significantly smaller areas. The calculation of Kappa statistics at 0.979, significantly above 0.8, supported the reliability of the LCM validation process.

The prediction accuracy for each LULC category shows that Water and Shrub have the lowest accuracies, at 89.61% and 81.54%, respectively. The accuracy for Water is close to 90%, which is considered a good level. The lower accuracy for Shrub is attributed to its relatively small area, with only 65 points involved in the validation process, where slight differences can lead to larger errors. Additionally, the validation results regarding the proportion of various LULC categories align with previous research (Yuan et al., 2020; Culbertson et al., 2016), indicating that the land pattern and development mode in the MRW have not significantly changed over the past 20 years.

Table 4 Confusion Matrix of LCM Validation:

		Actual Classification																	
Predicted Classification	Classes	N/A	WA	OS	LI	MI	HI	BA	DF	EF	MF	SH	GR	PA	AG	WW	EHW	Total	Accuracy
	N/A	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	100.00%
	WA	0	1277	0	1	1	1	3	8	1	0	1	5	3	6	21	97	1425	89.61%
	OS	0	0	6089	58	121	11	0	0	0	0	0	0	0	0	0	0	6279	96.97%
	LI	0	0	0	5680	39	28	0	0	0	0	0	0	0	0	0	0	5747	98.83%
	MI	0	0	0	0	3757	4	0	0	0	0	0	1	0	0	0	0	3762	99.87%
	HI	0	0	0	0	0	1655	0	1	0	0	0	0	0	0	0	0	1656	99.94%
	BA	0	0	0	0	1	0	243	0	0	0	1	2	0	2	1	3	253	96.05%
	DF	0	1	7	3	2	6	0	9770	0	3	22	32	14	17	0	3	9880	98.89%
	EF	0	0	0	0	0	0	0	0	184	0	0	2	0	0	0	0	186	98.92%
	MF	0	3	0	0	0	0	0	0	1	845	0	0	1	1	0	0	851	99.29%
	SH	0	0	0	0	1	0	0	2	0	0	53	0	4	5	0	0	65	81.54%
	GR	0	1	0	0	0	1	0	1	1	1	0	292	3	1	0	1	302	96.69%
	PA	0	3	23	44	93	33	0	11	0	0	3	4	5385	68	4	22	5693	94.59%
	AG	0	2	15	14	50	25	0	4	1	2	4	8	5	57077	8	13	57228	99.74%
	WW	0	13	3	3	1	0	0	3	0	0	0	2	0	1	5834	2	5862	99.52%
	EHW	0	1	0	0	0	3	0	0	0	0	0	0	13	1	26	752	796	94.47%
	Total	15	1301	6137	5803	4066	1767	246	9800	188	851	84	348	5428	57179	5894	893	100000	
	Accuracy	100.00%	98.16%	99.22%	97.88%	92.40%	93.66%	98.78%	99.69%	97.87%	99.29%	63.10%	83.91%	99.21%	99.82%	98.98%	84.21%		

Note: The table displays the correspondence between predicted and actual values for 100,000 randomly distributed points in the 2021 LULC map. From the table, we can deduce the prediction accuracy for each LULC classification. In the table, pink highlights the top 10% highest values within these LULC classifications, orange from dark to light correspond to the total number of each LULC classification from high to low, and blue from dark to light represent the prediction accuracy of each LULC classification from low to high. (The abbreviations for LULC classifications are as follows: N/A: Null Value; Water: WA; Open Space: OS; Low Intensity: LI; Medium Intensity: MI; High Intensity: HI; Barren Land: BA; Deciduous Forest: DF; Evergreen Forest: EF; Mixed Forest: MF; Shrub: SH; Grassland: GR; Pasture: PA; Agriculture: AG; Woody Wetlands: WW; Emergent Herbaceous Wetlands: EHW.)

3.3 Scenario Results & Discussion

3.3.1 Future LULC change under alternative scenarios

Figure 4 displays the net area changes of seven LULC types in the future five LULC scenarios compared to 2016, which is the LULC in S0. It is confirmed that the future development pattern of LULC involves a decrease in open space, pasture, and agriculture, and an increase in low intensity, medium intensity, and high intensity, with the changes in barren land being inconspicuous. This is consistent with historical trends. Among these changes, the variations in medium intensity, open space, and pasture are more pronounced. For S1, over the next 30 years, medium intensity is expected to increase by 33,022 acres, while open space and pasture are forecasted to decrease by 20,680 and 26,609 acres, respectively. The changes in the other three LULC types are relatively minor, with low intensity and high intensity increasing by 12,145 and 10,447 acres, respectively, and agriculture decreasing by 11,234 acres.

Comparing these five scenarios, it is found that in S2, compared to 2016, open space decreases by 10,720 acres, and medium intensity and high intensity increase by 19,931 and 8,523 acres, respectively. In contrast to S1, open space increases by 8,730 acres, while medium and high intensity decrease by 13,091 and 1,924 acres, respectively. This indicates that encouraging a low-intensity urban development model effectively protects open space in the future, while reducing the urbanization process of medium and high intensity. Moreover, compared to S1, pasture also increases by 4,194 acres in S2, thereby to some extent reducing the development of pasture. Changes in low intensity, barren land, and agriculture in S2 are not significant.

The results of S3 are almost the opposite of S2, with open space decreasing by 30,515 acres, and medium intensity and high intensity increasing by 19,937 and 12,598 acres, respectively. Compared to S1, open space decreases by 9,835 acres, and medium and high intensity increase by 14,695 and 2,151 acres, respectively, indicating that urbanization is further intensified under this scenario, aligning with the scenario's setup. Additionally, in S3, pasture and agriculture decreased by 30,785 and 13,389 acres, respectively, compared to S1, further decreasing by 4,176 and 2,155 acres.

Compared to 2016, in S4, open space, pasture, and agriculture decrease by 21,222, 26,060, and 11,182 acres, respectively, while low intensity, medium intensity, and high intensity increase by 12,408, 33,101, and 10,115 acres, respectively. The LULC changes in S4 are only slightly different from those in S2, indicating that the scenarios have essentially identical LULC changes. Thus, it is inferred that the scenario protecting pasture might not have a significant effect on mitigating water environmental issues at the watershed scale, but it cannot be excluded that this effect may be more significant at the subbasin or LSU scale.

S5, as an agricultural protection scenario, is the only one among the five scenarios where agriculture is expected to increase in the future, by 707 acres. Compared to S1, this scenario sees an additional 11,941 acres of agricultural land. Regarding urban LULC, in S5, open space decreases by 24,611 acres, while low intensity, medium intensity, and high intensity increase by 8,743, 30,837, and 8,492 acres, respectively. Compared to S1, the significant changes include decreases in open space, low intensity, and high intensity by 3,931, 3,402, and 1,955 acres, respectively.

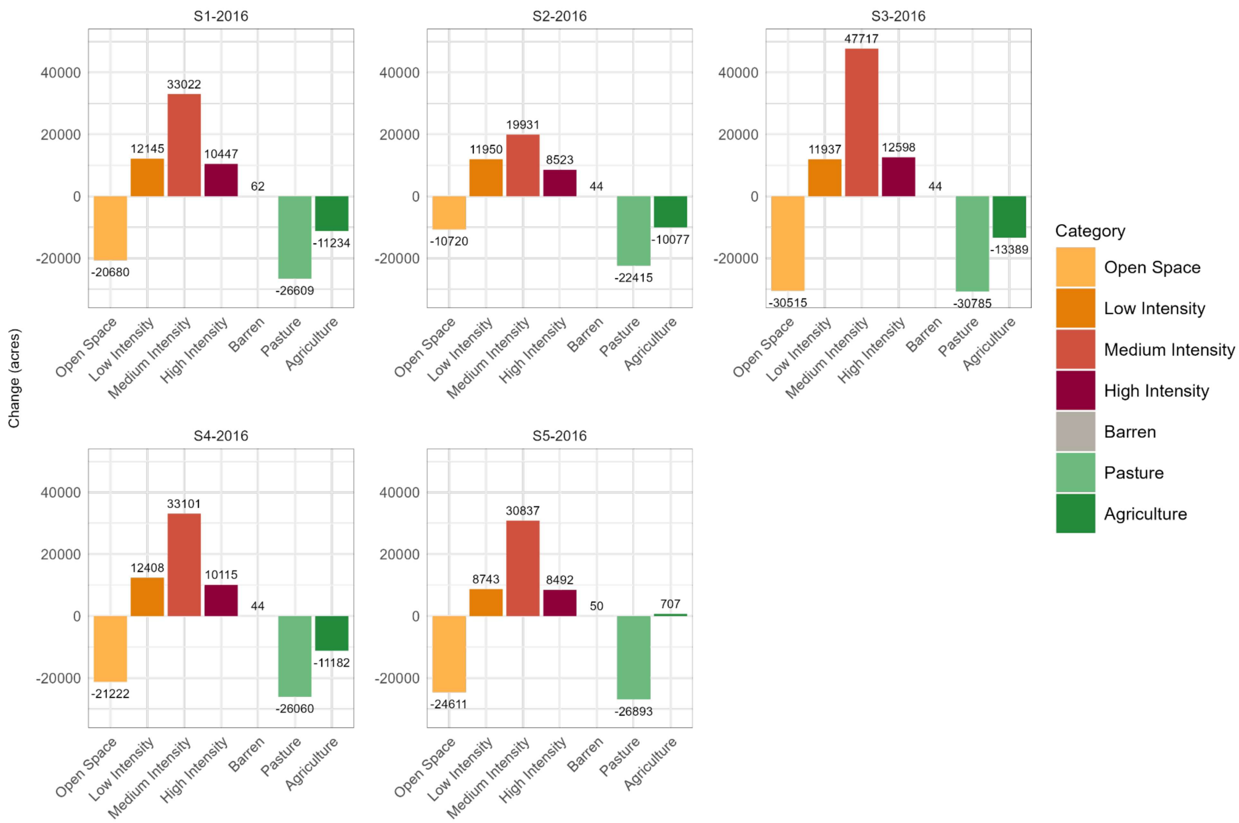


Figure 4. LULC Net Change of Five LULC Scenarios Compared with 2016: The five diagrams, arranged from left to right and top to bottom, sequentially display the net changes of seven LULC types in the S1, S2, S3, S4, and S5 scenarios compared to the year 2016.

The reasons behind the future LULC outcomes can primarily be attributed to two factors: the area proportions of various LULCs and the configuration mechanisms of the LCM. Given that the urban LULC proportion in the MRW is not particularly high, especially when compared to the highly urbanized Rouge River Watershed, there are no cities within MRW that exhibit exceptionally high levels of urbanization (Selzer and Bureau, 2008; Cipoletti et al., 2019). Although there are regions around MRW with relatively higher urbanization levels, such as Toledo, MRW only covers a small portion of these urban areas. Consequently, within MRW's urban LULC types, medium intensity has the highest proportion, and the most direct manifestation of urbanization in MRW is likely the increase in medium intensity areas, with open space being the primary source of this transformation. This explains why among the seven LULC categories, the changes in open space and medium intensity are very significant, while high intensity does not show particularly noticeable changes across the scenarios. The results for S2 and S3 are consistent with the LCM model settings, where S2 primarily reduces the transition from open space, low intensity, and barren land to medium and high intensity, effectively slowing down the urbanization process and preserving open space compared to S1.

In contrast, S3 increases such transitions, hence significantly exacerbating urbanization. The less desirable results for S4 could likely be due to the smaller proportional area and uneven distribution of pasture. Similarly, S5, due to the extremely high proportion of agricultural land, shows more significant effects. It's important to note that these diagrams only reflect the net change in overall LULC, so more pronounced changes might be present at the subbasin and LSU levels. Additionally, since the total area simulated at the county scale exceeds the MRW area, some regions are clipped in the process of generating the final watershed LULC map, which is another source of error.

3.3.2 Water Quantity and Quality Outcomes of Future Scenarios at Watershed Level

We calculated the differences in mitigation effects on Q, TSS, SRP, and TP among seven future scenarios (S1-S7) compared to the baseline scenario (S0) as depicted in Figure 5. Each scenario's boxplot in the figure reflects the collection of percent changes in mitigation effects for Q, TSS, SRP, and TP across 290 LSUs. Regarding Q, we found that the results for S1-S7 were similar, with ranges approximately from -1.0% to 1.5%, and the median slightly above 0. This suggests a slight and consistent increase in Q across the seven future scenarios. Notably, S1 and the two ACPs scenarios (S6 and S7), which all utilized the same 2046 LULC map, displayed nearly identical performances on Q. This indicates that enhancing no-tillage and reducing P fertilizer has negligible effects on surface runoff. Despite studies indicating that no tillage can reduce streamflow to some extent due to less soil disturbance thus enhancing the soil's infiltration capacity (Dick et al., 1989; DeLaune and Sij, 2012; Merten et al., 2015), the results in MRW, particularly for S6, were not significant. We attribute this primarily to the soil texture, as the low porosity of clay soils results in lower infiltration rates, thus the mitigation effect on Q is not pronounced (Uusitalo et al., 2000; Tan et al., 2002). S7 merely reduced soil nutrient inputs without altering the soil's physicochemical properties, hence its negligible impact on Q. However, there are slight differences in Q among the LULC scenarios (S1-S5), most notably, S3 showed a slight increase in Q compared to S1, while S2 showed a slight decrease. This can be primarily attributed to changes in LULC. Specifically, S3 significantly increased medium to high-intensity urban development areas, thus greatly increasing impervious surfaces such as concrete and asphalt, which in turn significantly increases the aggregation and velocity of surface runoff, thereby increasing Q, especially during rainfall (Chen et al., 2017; White and Greer, 2006; Olivera and DeFee, 2007). Conversely, the substantial reduction in urban density in S2 thus had better mitigation effects on Q, which also explains why all S1-S7 scenarios exhibit a slight increase in Q, as urbanized areas have increased overall compared to 2016 (Figure 4). However, the variation in urban areas did not result in significant changes in Q, likely due to the low proportion of urban areas in MRW.

The performance of S1-S7 on TSS showed more variability than Q (Figure 5). Overall, the mitigation effects ranged from -10% to 15%, with medians fluctuating around zero. ACP scenarios S6 and S7 performed similarly to S1, possibly because streamflow has not changed significantly, thus preventing the release of TSS from the soil (Hongbing et al., 2009; Poudel et al., 2010; Kamali et al., 2017). On the other hand, reduced soil disturbance, coupled with fine-textured soil, likely resulted in TSS being largely retained within the soil (Wang et al., 2014; Uusitalo et al., 2000; Carver et al., 2022). In the LULU scenarios (S1-S5), S2 and S5 had lower median TSS compared to S1, while S3 showed a slight increase. Additionally, except for S3, which showed an increased range, the other three scenarios showed a reduced range compared to S1. Despite the correlation between Q and TSS, as surface runoff carries TSS from agricultural fields, impermeable surfaces, and atmospheric deposition (Zhao et al., 2022; Charters et al., 2021), the results for S2 and S3 indicated that their Q and TSS trends do not align, with S2 showing an increase and S3 a decrease in median values. This may be due to S2 having increased open spaces, thereby caused more exposed soil and enhancing erosion, ultimately increasing TSS (Yazdi et al., 2021), while S3's decrease in open spaces leads to a slight reduction in TSS. For S4 and S5, although grazing activities intensify soil erosion and thus increase TSS content in runoff, and agricultural fields are inherently able to generate some TSS, MRW has historically implemented numerous BMPs on them to reduce TSS production (Amorim et al., 2020; Shigei et al., 2020; Chen et al., 2021). Therefore, TSS also decreased in S4 and S5, with S4 showing a less pronounced reduction mainly due to the relatively low proportion of pasture compared to agricultural land.

Regarding SRP and TP, we found a consistent trend across S1-S7, but the change in SRP was notably greater than that in TP (Figure 5). This indicates that future scenarios may result in little change in particulate phosphorus (PP), as TP is primarily composed of SRP and PP. Given the agriculture-based nature of MRW's LULC and the same settings of land management practices across scenarios, the impact of Q on PP was not significant across the watershed (Kamali et al., 2017; Uusitalo et al., 2000). A comparison across the seven scenarios revealed that S6's SRP and TP significantly increased, while S7 showed a significant decrease. This suggests that enhancing no-tillage substantially increases SRP and TP content in the water environment due to less soil disturbance, thereby retaining more residue on the agricultural field surface, which eventually enters the water (Muenich et al., 2016; Macrae et al., 2023). In contrast, S7 reduced P inputs at the source, thus significantly decreasing SRP and TP levels. Additionally, the results for SRP and TP in S6 and S7 did not align with changes in Q, indicating that in MRW, the impact of Q on SRP and TP is not as significant as that of ACPs. Comparing the five LULC scenarios, their results for SRP and TP showed little difference from each other but were substantially different from Q and TSS. This is mainly due to the large amount of P produced by agricultural land in MRW. Compared to S1, S2 and S5 showed a slight increase in SRP and TP, while S3 showed a slight decrease. This is likely due to the increase in open spaces in S2 leading to an increase in P, while the decrease in agricultural land in S3 led to a decrease in P, and S5 showed an increase due to increased agricultural land (Ahn and Mitsch, 2002; Rowland et al., 2019; Jarvie et al., 2017). S4 and S1 showed very similar performances in SRP and TP, likely due to the minimal difference in their LULC (Figure 4).

Overall, S1-S7 had no significant differences in the mitigation effects on Q and TSS, while ACP scenarios had a very apparent impact on water quality regarding SRP and TP. Therefore, we can conclude that the impact of ACPs on water quality is much more significant than that of LULC in MRW. Among the five LULC scenarios, S3 showed the best water quality mitigation effects, although it slightly increased the risk of urban flooding, while S2 showed the opposite effect. However, the essence mainly depends on the protective effectiveness of different scenarios on agricultural land. Besides, Figure 5 showed some outliers for each scenario, indicating that each scenario had some hydrological performances that did not align with LULC changes. We believe there are two main reasons for these deviations: one is model integration, that the LULC changes at the LSU level do not completely align with those at the county level. The other is that our focus is on results at water surface level, and underground hydrological performances may differ from surface results.

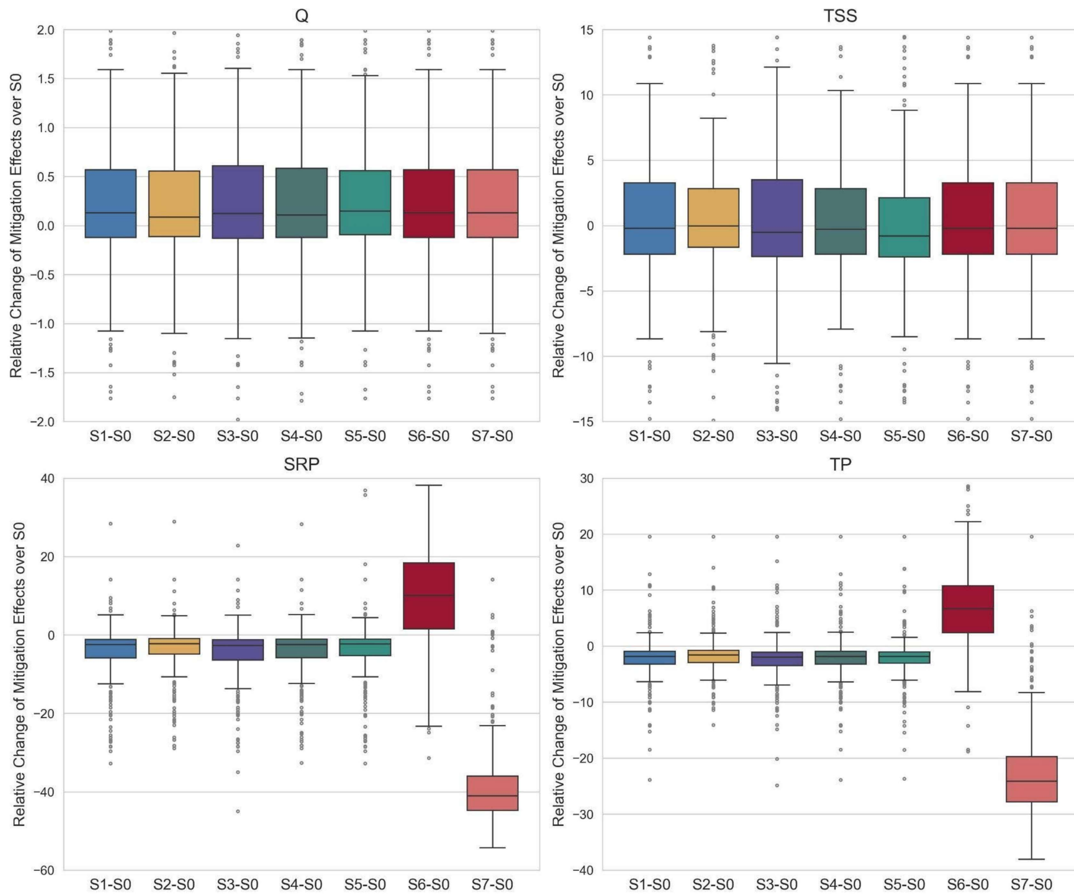


Figure 5. Change of Mitigation Effects For Future Scenarios over S0: Four boxplots sequentially display the percentage change in mitigation effects for future scenarios (S1-S7) compared to S0 in terms of Q, TSS, SRP, and TP. Top left: Change in mitigation effects for S1-S7 compared to S0 for Q; Top right: Change in mitigation effects for S1-S7 compared to S0 for TSS; Bottom left: Change in mitigation effects for S1-S7 compared to S0 for SRP; Bottom right: Change in mitigation effects for S1-S7 compared to S0 for TP.

3.3.3 Monthly Mitigation Effects Across Future LULC Scenarios

To better explore the impact of LULC on streamflow and water quality in the MRW, we analyzed the performance of scenarios S1-S5 in terms of Q, TSS, SRP, and TP on a monthly scale during the period from 2046 to 2065 (Figure 6). S0 was not considered because S1-S5 are LULC scenarios that envision the trend of different LULC types in the future. Figure 6 showed the monthly differences in Q, TSS, SRP, and TP for the average future of each month, and monthly climate data variations were also included. Overall, we observed that the trends of Q, TSS, SRP, and TP throughout the year were generally similar across scenarios, with a noticeable decrease from June to September and a gradual increase from October to January. Q and TSS, SRP, TP generally showed a decreasing trend from February to May, but there were some variations, specifically a noticeable decrease in TSS, SRP, and TP in March and April. The overall trends in

Q, TSS, SRP, and TP are likely due to seasonal climatic changes and nutrient dynamics in the MRW (Moog and Whiting, 2002; Gildow et al., 2016; Culbertson et al., 2016). There is a clear correlation between Q and weather, with a significant increase in surface runoff from October to January due to increased precipitation and lower temperatures. Although precipitation increases from February to July in the MRW, the rise in temperature causes more snowmelt, increasing Q in February and March, while the warming starting in April directly leads to increased transpiration (Wang et al., 2023).

Regarding TSS, SRP, and TP, their variations are to some extent correlated with Q. This is mainly because an increase in surface runoff intensifies the erosion of land around rivers and carries more pollutants produced by urban areas, thereby increasing the levels of TSS, SRP, and TP in the water (Gnecco et al., 2005; El Kateb et al., 2013; Tibebe and Bewket, 2011). Higher streamflow also stirs up sediments settled at the bottom of water bodies, increasing concentrations of TSS and phosphorus (Du et al., 2022; Zanon et al., 2020). Additionally, more precipitation also washes pollutants from farmlands and urban surfaces into the runoff (Yang et al., 2021). The noticeable decrease in TSS, SRP, and TP in March and April is mainly attributed to agricultural activities. Some regional soil tilling transfers surface nutrients into deeper soil layers, reducing nutrient loss by surface runoff. The growth of crops also reduces levels of SRP, TP, TSS mainly through crop absorption, root stabilization of soil which reduces erosion and nutrient transport and serving as ground cover to lessen the erosion of rain and runoff (KC, 2021; Richards et al., 2010; Bosch et al., 2014).

Comparison of S1-S5 shows almost no significant differences among these scenarios. The slight differences mainly reflect an increase in SRP and TP in S2 and a decrease in SRP and TP in S3 and S5, consistent with previous conclusions. Thus, aside from the overall similar trend on a temporal scale among the different LULC scenarios in the watershed, there are no significant month-by-month differences among them. This also indicates that changes in different LULCs do not significantly differ in their mitigation effects on MRW seasonally.

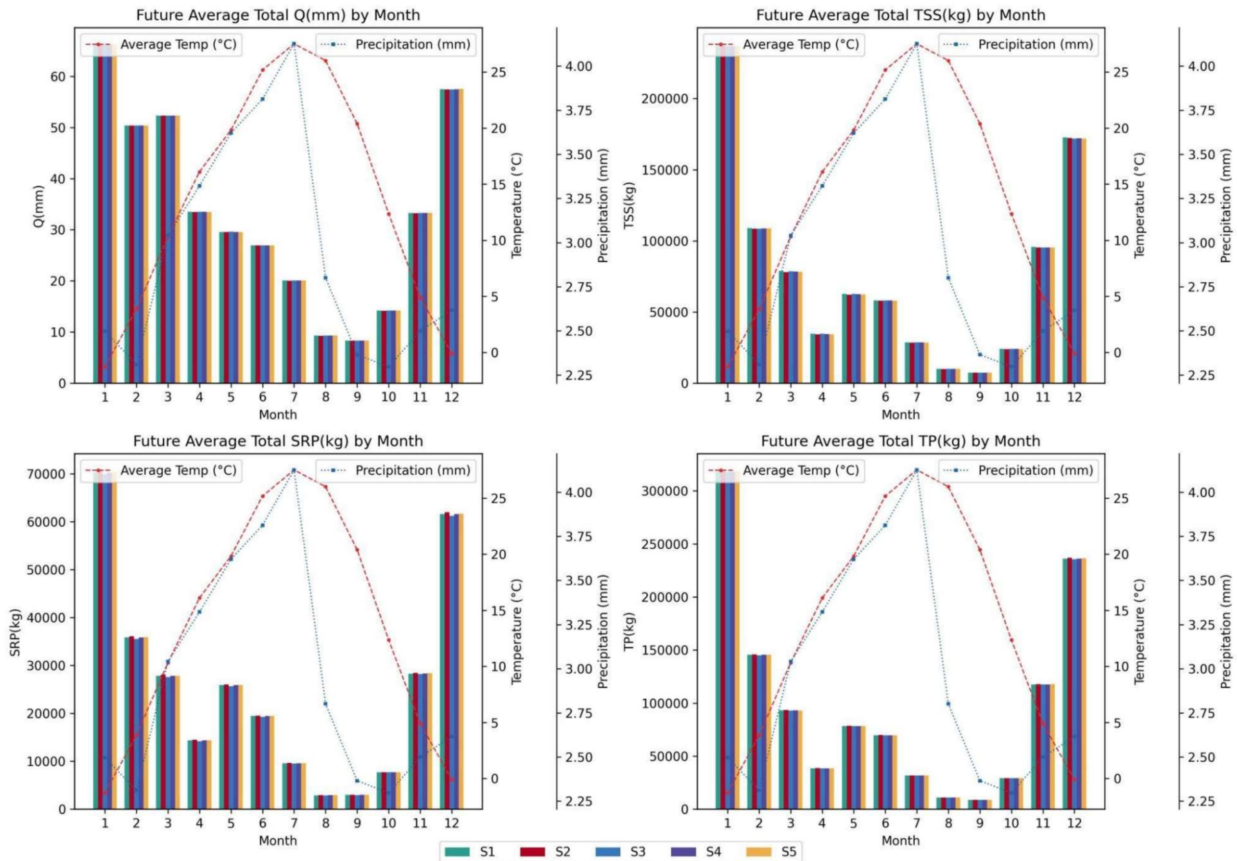


Figure 6. Comparison of Average Mitigation Effects across Urban Scenarios (S1-S5) by Month: The bar chart shows the difference in average monthly mitigation effects between S2-S5 and S1 for the years 2046-2065. The line graph displays the average monthly climate data changes for the same period, where the red dashed lines represent the average monthly temperatures (°C), and the blue line represents the average monthly precipitation (mm). (a) Difference in Q (mm) on average each month between S2-S5 and S1; (b) Difference in TSS (kg) on average each month between S2-S5 and S1; (c) Difference in SRP (kg) on average each month between S2-S5 and S1; (d) Difference in TP (kg) on average each month between S2-S5 and S1.

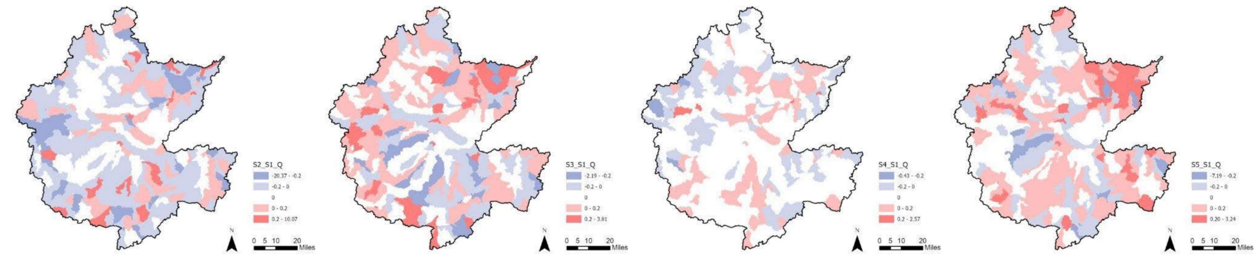
3.3.4 Water Quantity and Quality Outcomes of Future Scenarios at LSU Level

To better explore the spatial scale impacts of LULC changes on Q, TSS, SRP, and TP, we compared the mitigation effects of S2, S3, S4, and S5 against S1 across different regions of the MRW. Figure 7(a) showed the spatial differences in Q for the LULC scenarios, where purple indicates areas with better mitigation effects compared to S1, and red indicates worse areas. We found that S2 had the most purple areas while S3 and S5 had relatively higher red areas. This is mainly attributed to the correlation between four types of urban LULC and Q, where an increase in open space leads to a decrease in Q, an increase in medium and high-intensity urban land leads to an increase in Q, and low-intensity urban land has a negligible impact on Q (Figure 8). Although this correlation is not pronounced in MRW, possibly due to the overall small urban area, as scatter plots also involve some LSUs predominantly agricultural land. Based on this correlation, S1 is the most effective in mitigating Q since it significantly protects open space. S3, which promotes the development of medium and high-intensity LULC, is not effective in mitigating Q. S5, despite reducing some medium and high-intensity urban land, also reduces some open space, thus its mitigation effect on Q is not significant. S4, having a similar LULC pattern to S1, shows many blank areas in the figure, and some LSUs in the northwest part of the watershed with a higher proportion of pasture show certain mitigation effects on Q compared to other scenarios due to the preservation of pasture area. Additionally, the mitigation effects of S2 and S3 on Q are inconsistent in the major urban areas of Toledo in the northeast and Fort Wayne in the west of MRW, indicating that S2 is likely very effective in mitigating Q in heavily urbanized areas. This mitigation is presumed to be partly through reducing medium and high-intensity urban land to decrease the urban heat island effect thus reducing rainfall intensity (Zhao et al., 2014; Steensen et al., 2022) and partly by promoting runoff infiltration in open spaces to reduce streamflow (Franzen et al., 2020).

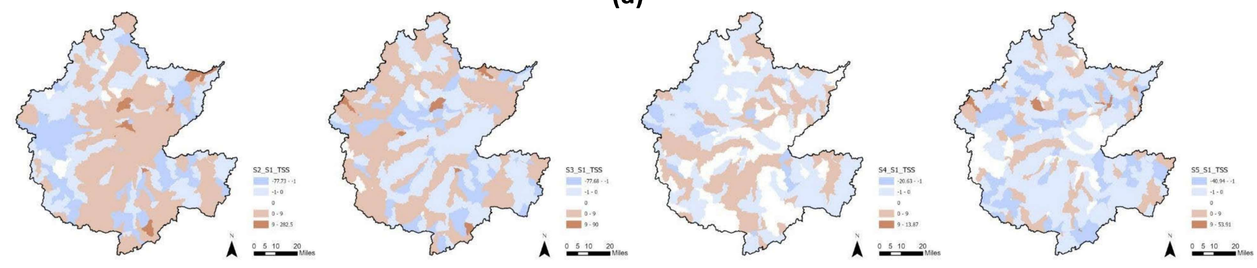
Figure 7(b) shows the distribution of differences in TSS mitigation effects of S2-S5 compared to S1, where blue indicates areas with better mitigation effects, and brown indicates worse areas. It is observed that S2 has better TSS mitigation effects in urban areas, while its mitigation effects are not ideal in the central agricultural regions. S3 shows better mitigation effects in some central areas but does not effectively mitigate TSS in urban areas. S4's mitigation effects on TSS are primarily evident in the northwest part of the watershed. Combined with previous analysis, S5 not only mitigates the total amount of TSS but also has a broader distribution range of this effect. Additionally, we find that there is still some correlation between Q and TSS in urban areas like the northeast and west of MRW, as Q can wash off urban surfaces and carry away a significant amount of TSS. However, this correlation is not evident in less urbanized areas, such as some central LSUs in S2 and S3, where even if Q decreased, TSS increased. This is mainly because S1 and S2, while adjusting urbanization in urban areas, also increase various types of urban land in non-urbanized areas, thus leading to an increase in TSS. While S1, mainly due to significant increase in open space, does not show good mitigation effects on TSS in central areas. S5, although increasing agricultural land, benefits from MRW's long-standing ACPs, thus the increase in agricultural land does not lead to an increase in TSS (Fraker et al., 2023; Tuppad et al., 2010; Barrett, 2008).

Figure 7(c) and Figure 7(d) show the distribution of differences in SRP and TP mitigation effects of S2-S5 compared to S1, where blue indicates areas with better mitigation effects, and orange and red indicate worse areas. Additionally, the correlation between various LULC changes and SRP was analyzed across 290 LSUs (Figure 9). From Figure 7, it is evident that S2's SRP and TP exhibit poorer mitigation effects across most of the watershed, possibly due to the reduction in medium to high-intensity urban areas, which are negatively correlated with SRP as demonstrated in Figure 9. Moreover, although there is no direct correlation between open spaces and SRP, studies indicate that an increase in open spaces, which not only intensifies soil erosion but also increases SRP and TP levels if vegetation management measures are not effectively applied (Toland et al., 2012; Brezonik and Stadelmann, 2002). The increase in open space in urban areas also leads to streamflow carrying more PP, resulting in some urban areas in the northeast and west of MRW having a significantly lower mitigation effect on TP compared to SRP (Brezonik and Stadelmann, 2002; Chow and Yusop, 2014). In contrast, S3 appears to be the most effective scenario among the five LULC scenarios in reducing SRP and TP. This is partly because, compared to S1, S3 does not significantly increase open space and, compared to other scenarios, S3 also reduces agricultural land. Given the strong positive correlation between agricultural land and SRP (Figure 9), the reduction in agricultural land in S3 directly leads to a decrease in SRP. While ACPs can effectively reduce nutrients produced by agriculture, the inevitable application of manure and fertilizers in agricultural activities, as well as soil disturbance from tillage practices, still increases P outputs (Sohoulande et al., 2023; Gildow et al., 2016; Moore et al., 2005; Anderson et al., 2020). This also explains why many areas in S5 show poor mitigation effects on SRP and TP. Comparing the distribution of SRP and TP, it is not difficult to observe that the mitigation effects on TP are significantly less than SRP in most areas. One reason is that the extensive application of manure and fertilizers on agricultural land and pasture is likely causing most of the P in the soil to be bound to soil particles (DeLaune et al., 2006; Walling et al., 2008). Therefore, S4, due to protecting pasture in the northwest part of MRW, shows significantly worse mitigation effects on TP compared to SRP in that area. Similarly, the extensive farmland in the central part of S5 also results in less-than-ideal mitigation effects on TP.

Overall, the spatial distribution differences of the five LULC scenarios are more pronounced than the temporal and quantitative differences. Besides the certain connection between Q and TSS, SRP, TP, the LULC properties of each scenario seem to be more important. From the results, S2 is more effective in mitigating Q, S5 is more effective in mitigating TSS, and S3 is more effective in mitigating SRP and TP. However, the focus areas of different scenarios also vary, for example, S2 shows better TSS mitigation effects in the Fort Wayne area in the west of MRW compared to S5, S3 shows better mitigation effects on Q in the northwest part of MRW.



(a)



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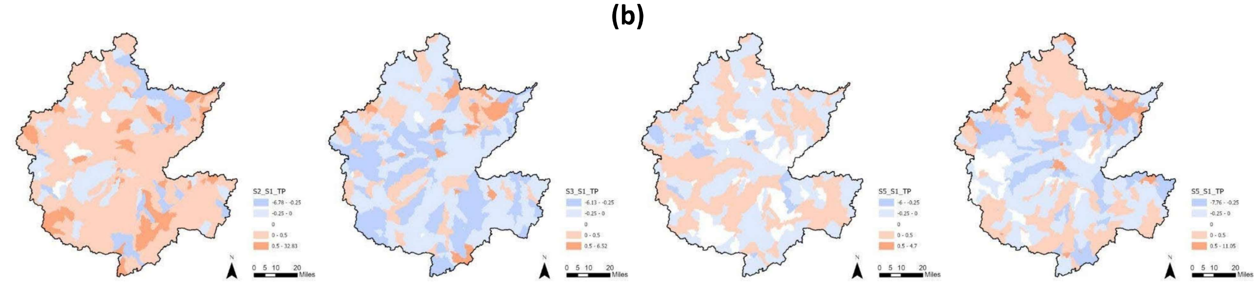
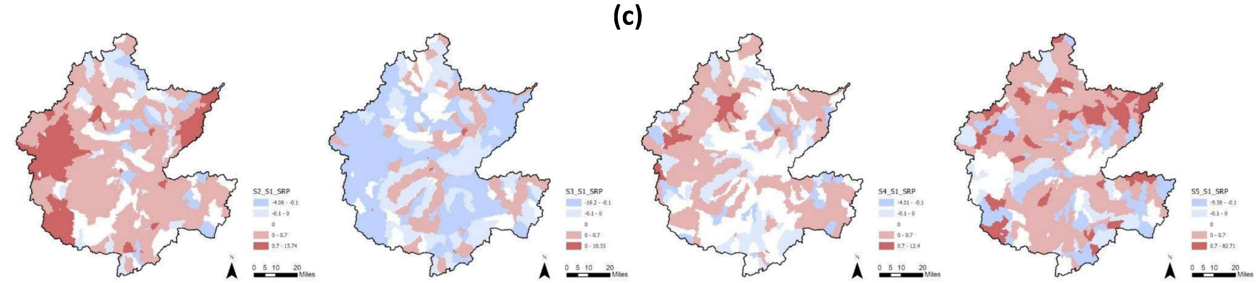


(c)



(d)

Figure 7. Spatial Distribution of Mitigation Effects of Four Urban Scenarios (S1-S4) over S0: The diagrams separately show the spatial variation in the differences in Q, TSS, SRP, and TP between S2-S5 and S1. The blue hues represent areas where the water environment has improved in S2-S5 compared to S1, and the red hues indicate areas where the water environment has worsened. (a) Spatial variation in the mitigation effects on Q between S1-S4 and S0; (b) Spatial variation in the mitigation effects on TSS between S1-S4 and S0; (c) Spatial variation in the mitigation effects on SRP between S2-S5 and S1; (d) Spatial variation in the mitigation effects on TP between S2-S5 and S1.

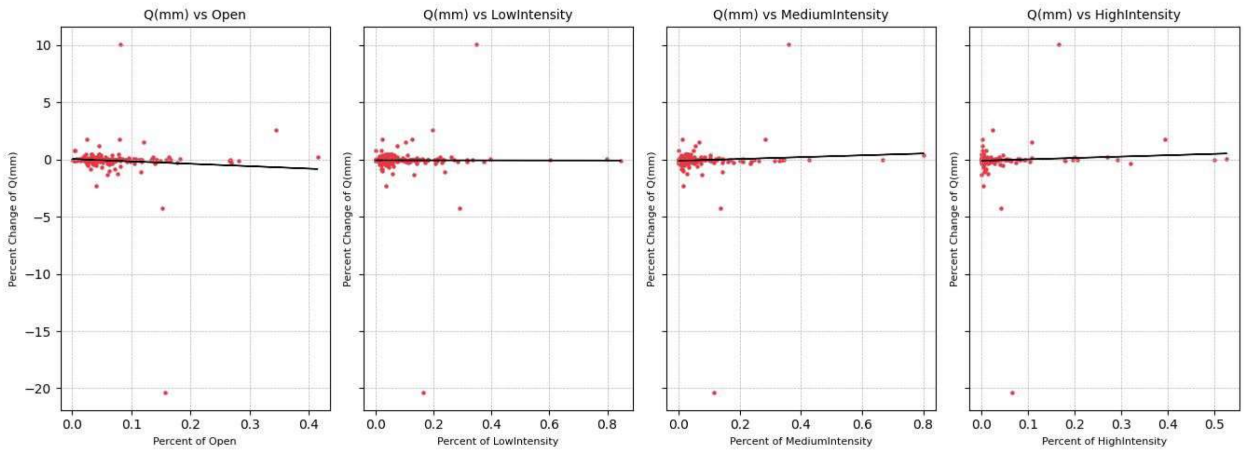


Figure 8. Scatterplots of percentage change in Q with urban LULCs for S2 Compared to S1: The four scatterplots sequentially display the correlation between the percentage changes in Q and the changes in four types of urban LULCs (open space, low intensity, medium intensity, and high intensity) for S2 compared to S1.

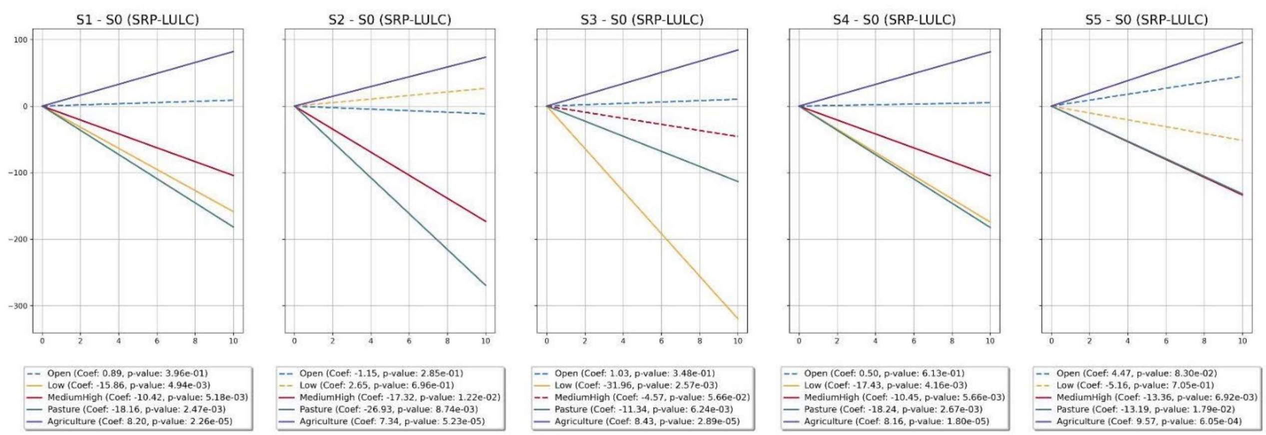


Figure 9. Diagrams of Correlation between SRP and LULCs: Five diagrams sequentially show the changes in five types of LULC (open space, low intensity, medium & high intensity, pasture, agriculture) compared to S0 and the changes in SRP. Solid lines represent correlations with a p-value less than 0.05, which is statistically significant, while dashed lines indicate no statistical significance. Here, we combine medium intensity and high intensity because these two LULC categories exhibit strong collinearity in multiple regression analysis.

3.4 Implications

Combining ACPs with LULC scenarios, reducing the application of P fertilizers on agricultural lands is a critical strategy for alleviating water quality issues in the MRW. Furthermore, from a temporal perspective, the accumulation of TSS, SRP, and TP primarily occurs from winter to early spring. Therefore, implementing winter cover crops to mitigate nutrient loadings during the winter season is essential. In terms of LULC, moderately increasing open spaces can reduce streamflow to some extent. If further strategies such as community gardens, stormwater management, and ecological diversity restoration are applied to open spaces, it can significantly enhance the interception of streamflow and TSS (Xue et al., 2017; Gómez et al., 2013). Regarding SRP and TP, which significantly impact water quality, especially in relation to HABs, increasing the area of various urban LULCs while decreasing agricultural land seems to be an effective strategy. Specifically, this could involve increasing open space and low-intensity areas in suburban regions or adding medium to high-intensity urban areas in highly urbanized areas. However, this increase must be moderate, as excessive urbanization could lead to more point-source pollution. This relatively centralized urban development model facilitates concentrated energy use and centralized pollution management.

Additionally, in urbanized areas, encouraging the construction of green infrastructures such as green roofs, rain gardens, and permeable pavements can help absorb and filter runoff, thereby reducing the phosphorus loadings that reach water bodies. These strategies collectively represent a comprehensive approach to managing land use and environmental conservation to protect water quality in the MRW. Therefore, the future development patterns of the watershed could follow several basic directions: 1) appropriately increase development intensity in highly urbanized areas to meet the growing economic and population demands; 2) in less urbanized areas, appropriately increase open spaces with appropriate management practices ; 3) combine actual agricultural production needs with measures such as returning farmland to forests or water bodies. Of course, these strategies are essentially based on the specific LULC conditions and policies of different regions.

3.5 Limitations

Given the complex mechanisms of LULC changes, our study possesses several limitations. Firstly, our scenario settings for future LULC are based on trends over the past decade, focusing primarily on the most significantly changing LULC types such as urban areas, pasture, and agricultural land. Other LULC types like forests, shrubs, and water were maintained with their existing transition probabilities without explicit scenario incorporation. Additionally, the scenario design is not closely integrated with local policies. Secondly, in the integration process of the LCM and SWAT+ models, discrepancies arise as county boundaries do not align perfectly with LSUs. Therefore, LULC changes at the LSU scale may not fully reflect county-level LULC transitions. Analytically, our study concentrates solely on surface aspects of Q, TSS, SRP, and TP, omitting subsurface hydrological conditions. Moreover, given that the LULC and hydrological changes across the 290 LSUs do not follow a uniform pattern, our analysis could only globally evaluate their performance under different scenarios at temporal and spatial scales. Other limitations include minor nutrient inputs involved in urban LULCs and changes in point-source pollution resulting from urban LULC alterations, which were not considered in our model settings. Additionally, inherent inaccuracies in model algorithms and input data contribute further to the study's limitations.

Chapter 4: Conclusion

LULC scenarios have definite mitigation effects on the water environment of MRW, with particularly noticeable effects on Q. Among these, the low-intensity development scenario S2 shows the best mitigation effects. In terms of water quality, ACPs Scenarios demonstrate more distinct performances compared to LULC scenarios, with S7—which reduces phosphorus fertilizer—showing the best mitigation effects on P. However, the performance of the five LULC scenarios on P is similar, with the compacted development scenario S3, which encourages the development of medium and high-intensity, performing the best. Regarding TSS, we conclude that the agriculture protection scenario S5 shows slightly better mitigation effects. We also observe that the overall differences of the five LULC scenarios in their mitigation effects on water environment are less pronounced in terms of quantity and time compared to spatial scales. Concerning LULC categories, open space and agricultural land have the most significant impacts on the water environment in the watershed. Therefore, to meet agricultural and economic needs, appropriately increasing the development intensity of highly urbanized areas and open spaces in urban and suburban areas, while reducing some agricultural areas, can effectively mitigate future water environmental issues in the MRW. However, these strategies are all based on reducing fertilizer input from agricultural land and implementing reasonable management practices for open spaces. Nonetheless, the overall planning of the watershed down to the scale of different counties should also take into account the specific LULC types and patterns as well as relevant policies of each county, with a targeted analysis for specific issues.

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