Understanding Stream Water Quality and Fish Diversity in the Great Lake Surrounding Areas: A Path Modeling Analysis

by

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Abstract

Fish richness and diversity serve as important indicators of a healthy stream ecosystem, which are influenced by a complex web of ecological factors, including regional climate, watershed characteristics, riparian zone quality, and water quality. Investigating how these factors interconnect and impact fish community is crucial for developing effective management strategies to safeguard freshwater ecosystems. In this study, we used partial least squares regression to develop a causal understanding of how watershed development and climate factors affect fish richness and diversity by altering water temperature, pH, conductivity, total nitrogen, and total phosphorous (TP) in 277 watersheds in the Great Lake surrounding areas. After identifying TP as a potential threat to fish biodiversity, we examined how watershed land use, slope, and soil interacted to drive changes in TP concentration with multiple linear regression. Results suggested that moderate watershed development (average 5% developed percentage in the study site) can enhance fish diversity by increasing pH, temperature, and conductivity. However, watershed development and riparian degradation diminished fish diversity by increasing nutrient concentrations. We also found that land cover-slope interaction was an important factor affecting TP concentration, while land cover-soil interaction was not significant. Future ecosystem management in the study area should therefore emphasize a dual focus on watershed management approaches and riparian zone preservation to improve fish diversity and stream ecosystem health.

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Chapter 1: Introduction

Fish diversity and richness are vital indicators of biodiversity and ecosystem health, where species with greater diversity and richness adapt to a wider variety of conditions such as stream disturbance, disease, and climate change (Hiddink et al., 2018; Messemer et al., 2011). Fish diversity and richness also influence various ecosystem services including aquatic habitat, recreational opportunities, and fisheries (Keeler et al., 2012; Prudencio and Null, 2018). Today, freshwater fish population are increasingly jeopardized by human activities, primarily due to factors such as river fragmentation, habitat loss, eutrophication and pollution, and the introduction of non-native species (Su et al., 2021). These threats manifest at different spatial scales, ranging from global climate change, watershed-scale land use change, and riparian scale stream degradation, to in stream-scale change in water physiochemistry. Such threats induce alterations in fish diversity and richness predominantly by modifying the freshwater environment, including temperature, nutrients, sediment, and toxins (Keeler et al., 2012). To the best of our knowledge, little research has been done to investigate this complex system at cross scales to identify the pathways of fish diversity alteration.

Threats to freshwater fish diversity and richness could be causally and structurally linked. For example, the combined effect of watershed development and climate change causes flow regimes alteration and generates greater sediment and nutrients under heavy rainfall events, thereby driving changes in habitat suitability and fish community composition (Ferreira et al., 2019; Pörtner and Peck, 2010; Turunen et al., 2021). Another possible pathway is that damage to riparian vegetation affects fish biodiversity by altering sedimentation, nutrients, and water temperature (Wilkinson, 1999). Two major gaps are associated in quantifying these pathways and their effects on fish richness and diversity. Firstly, there is limited understanding of the relative importance of the threats to fish richness and diversity in a specific ecological context. For example, it remains unknown whether watershed land use change or riparian zone alteration are more influential, since both alter runoff patterns, sedimentation, pollution, and habitat suitability; and the relative importance may vary depending on the characteristics of the freshwater system (Meador and Goldstein, 2003). Secondly, the effect of a specific pathway changes according to environmental conditions. For instance, the disturbance of riparian zone is typically considered harmful to fish diversity as it undermines a diverse range of habitats, elevates soil erosion, and increases water temperature (Reid et al., 2019). While the intermediate disturbance hypothesis suggests local species diversity is maximized in the intermediate disturbance condition, moderate disturbed riparian zone has high biomass due to the abundance of terrestrial and aquatic food availability (Albertson et al. 2017). Therefore, a causal model is needed to quantify the strength and effect of different pathways on how watershed characteristics, riparian quality, as well as water physical, chemical, and biological indicators are intertwined in their effect on fish richness and diversity. Wang and colleagues (2021) have recently applied a structural equation model to water quality because of its advantage in constructing latent variables using measured variables and exploring the causal pathways; however, this model has been rarely used to investigate fish diversity.

Understanding the change of nutrients is fundamental to investigating fish diversity because high TP concentrations in streams can reduce fish diversity by promoting algae growth, thereby reducing oxygen levels and creating unfavorable conditions for fish (Dala-Corte et al., 2016). Extensive literature on the drivers of total phosphorus (TP) concentration in surface water has identified multiple drivers of phosphorus pollution, such as climate change, geology, soil type, topography, landscape composition, landscape configuration, seasonal land use change, and catchment hydrology (Lintern et al., 2018). Past research selected appropriate variables from these drivers to model in-stream TP concentration; however, conclusions regarding the effect of each driver were inconsistent. Some researchers proposed that flat areas may discharge more nutrients when compared to steep areas (Yu et al., 2016), while others suggested that a decreased deviation in slope is associated with a decrease in pollutant concentration (Wang et al., 1997; Wissmar et al., 1990). These inconsistent conclusions may be due to interaction effects between variables having been often overlooked, especially how land cover interacts with other geophysical factors in influencing TP (Kaushai et al., 2008).

Slope and soil are key factors that interact with land cover in affecting water quality (Yu et al., 2016). Slope is an important factor affecting nutrient concentration in the water body because it is related to surface runoff volume and velocities. Slope was also identified as a key parameter in predicting rates of water flow across surfaces (Richards et al., 1996). With increasing slope, greater rates of water flow contribute to soil erosion and the rates of particulates picking up pollutants, which has the potential to further deteriorate water quality (Yu et al., 2016). The chemical characteristics of soil (e.g., phosphorus, nitrogen, and salt content in soil) directly affect the types and concentration of pollutants in water (Dillon et al., 1975). Soil erodibility and sorption capacity also influence constituent mobilization in catchments (Lintern et al., 2018). The mobilization of sediments is positively correlated to the susceptibility of the geological deposit and the soil within the catchment to erosion and weather. Moreover, soil hydrological property affects water quality, with a lower hydraulic conductivity leading to more residence time of subsurface flow and facilitating pollutants to be removed by vegetative uptake or biogeochemical processing (Lintern et al., 2018). As a result, research has found a positive correlation between pollutants in water and soil drainage capacity (Arheimer et al., 2000; Franklin et al., 2013).

In this study, we hypothesized a causal connection between watershed development, climate, and fish community, with riparian quality and water quality as mediating factors. Stream nutrients are affected by watershed development through a combination of land use, topography, soil, and their interaction effects. Our specific research goals are as follows: (1) to explore the spatial distribution of important land cover, climate, riparian quality, water quality, and fish diversity variables and their associations; (2) to investigate the mechanisms by which watershed development and climate impact fish richness and diversity; and (3) to assess how land cover-slope interaction and land cover-soil interaction affect TP concentration.

Chapter 2: Materials and Methods

2.1 Study Site

We obtained our sampling stations from the EPA's National River and Stream Assessment (NRSA) between 2018-2019 as part of the National Aquatic Resource Surveys. We defined the site as all states surrounding the Great Lakes (i.e., Illinois, Indiana, Michigan, Minnesota, New York, Ohio, Pennsylvania, and Wisconsin), resulting in the sample size of 277 stations. We delineated subwatershed boundaries with the location and elevation of these stations as shown in Fig. 1 with ArcGIS (version 10.8). The major land use types of our study area are forest and cropland. All samples were collected in summer with an average daily temperature of 19.9°C in the area.

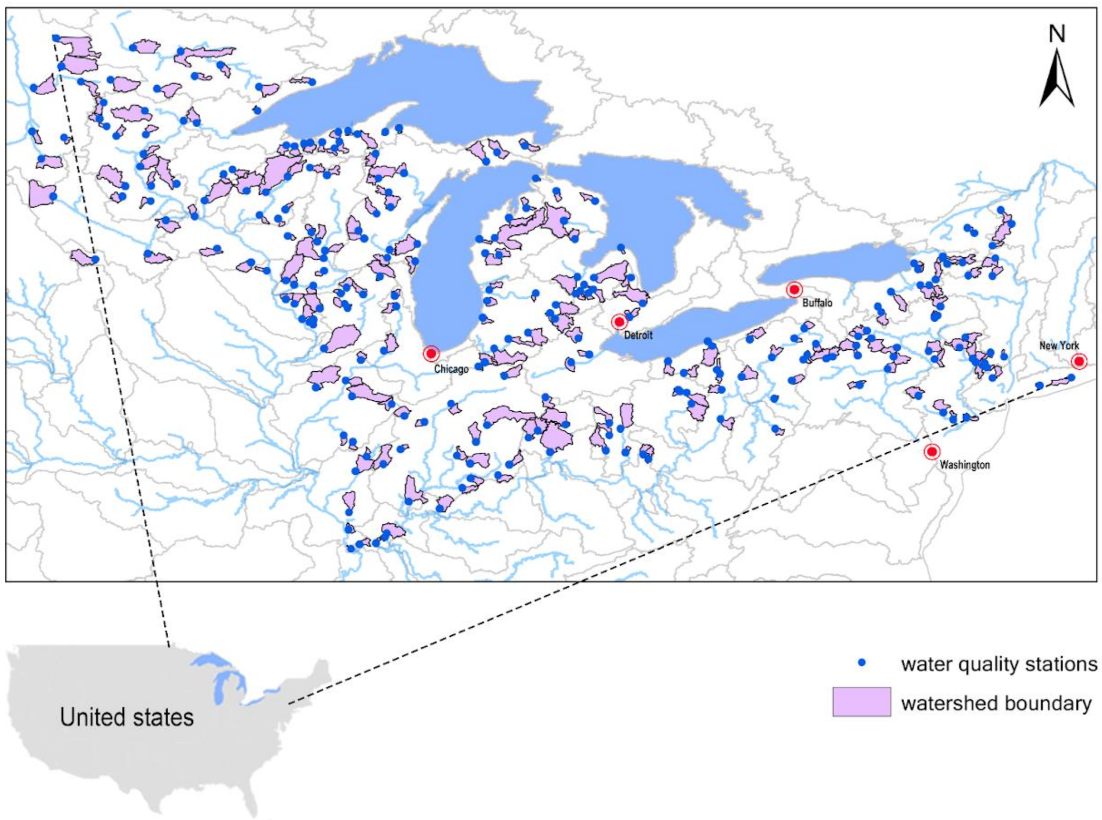

Fig. 1. Study site.

2.2 Data and Variables

Fish community data were obtained from NRSA 2018-2019; and we calculated the richness and Shannon diversity index based on the number of each fish species, which represented fish community structure (J Zhao et al., 2014). Here, H is the Shannon diversity index, and P(i) is the proportion of each fish species (Eq. 1):

$$H = -\sum_{i=1}^{n} [P(i) * lnP(i)] \quad (1)$$

Water quality data included TP, total nitrogen (TN), pH, conductivity (COND), and water temperature (WATER_TEM). Phosphorus and nitrogen are the main nutrients associated with the intensification of cropland in the catchment area, which could have significant negative impact on aquatic ecosystems function (Owens et al., 2005; Bierschenk et al., 2019). pH, COND, and WATER_TEM are water quality parameters highly relevant to fish diversity, as changes in these indicators may influence the transmission of acoustic, visual, and chemical signals, thereby affecting species interactions and reproductive success (Barrella et al., 2003; Leuven et al., 1987).

Climate data were obtained from the parameter-elevation relationships on independent slopes model dataset, which provides gridded climate datasets for the United States (Daly et al., 2008). Among climate variables, we calculated the daily precipitation amount and daily average temperature at the subwatershed scale to match the TP concentration collected from the outlet of the subwatershed (see Table 1). We also calculated the monthly maximum 1-day precipitation (Rx1day), warmest monthly temperature, and coldest monthly temperature to represent the extreme climates effect on water quality and fish. Rx1day was calculated using Eq. 2, where Rx1dayj is the maximum 1-day precipitation value for period j, and RR_{ij} is the daily precipitation amount on day i in period j:

$$Rx1day_j = max\ (RR_{ij}) \quad (2)$$

Land cover percentages were obtained from the National Land Cover Database (NLCD; 2019), a 30m Landsat-based land cover database. These images rely on the imperviousness data layer for urban classes and on a decision-tree classification for all other classes (Dewitz et al., 2021). Among the various land cover types, we selected the percentage of developed, agricultural, and forest land as variables to represent watershed development conditions. NLCD divides the developed area into four categories: (1) developed open space (impervious surfaces <20%); (2) developed low intensity (impervious surfaces 20%-49%); (3) developed medium intensity (impervious surfaces 50%-79%), and (4) developed high intensity (impervious surfaces >80%). It divides forest land into three categories: (1) deciduous forest; (2) evergreen forest; and (3) mixed forest. To simplify the model, we merged the developed low, medium, and high intensity into developed ("DEV") land and combined all types of forest into a single "FOREST" category. The developed open space remained a separate category because the impervious percentage was lower than 20% and not likely to cause stream syndrome (Walsh et al., 2015).

Soil type were obtained from the OpenLandMap Soil Texture Class (USDA System). Because the water quality indicators we used were primarily pollutants transported with surface runoff, we used the 0cm soil depth layer as the soil data source. We then reclassified the 12 types of soil into three different types (clay, silt, and sand) according to the soil textural triangle. Silt and sand had a strong correlation, while sand and clay had a weak correlation. Therefore, we chose sand and clay as variables to represent soil texture in our study and excluded silt. Slope variable were calculated based on the 30m-resolution NASA digital elevation model.

Part of the riparian zone variables were from NRSA, including riparian quality index, riparian vegetation quality index, and riparian disturbance index. These represented on a scale from 0 to 1 the quality and disturbance of the riparian buffer. Other riparian zone variables including proportion of deciduous forest (R_DECI), evergreen forest (R_EVER), and mixed forest (R_MIXED) in riparian zone were calculated from NLCD 2019. Specifically, we calculated the fraction of different forests at the riparian buffer scale defined as 500m surrounding the water quality stations. Here, we separated forest categories because different forest species and defoliation along the riparian buffer could have varying impacts on fish diversity (Allan et al., 2004).

Table 1. Variables used.

Variable	Description	Units
Fish community variables		
Richness	Abundance of fish species around each water quality station	/
Diversity	Shannon diversity index (H) of fish community	/
Water quality variables		
TP	Total phosphorus	ug / L
TN	Total nitrogen	mg / L
PH	Potential of hydrogen	/
COND	Conductivity	uS / cm
WATER TEM	Water temperature	°C
Climate variables		
TMEAN	Daily average temperature	°C
PPT	Daily total precipitation	mm
W MTEM	Warmest monthly temperature	°C
C MTEM	Coldest monthly temperature	°C
Rx1day	Monthly maximum 1-day precipitation	mm
Land cover variables		
OPEN	Proportion developed open land (impervious surface <20%)	%
DEVELOPMENT	Proportion developed land (impervious surface >20%)	%
FOREST	Proportion forest land	%
CROP	Proportion agricultural land	%
Slope variables		

SLOPE	Average slope	%
Soil variables		
CLAY	Proportion clay in soil	%
SAND	Proportion sand in soil	%
Riparian zone variables		
QR	Riparian quality index	/
QRVeg	Riparian veg quality index	/
RDIST	Riparian disturbance index	/
R_DECI	Proportion deciduous forest in riparian zone	%
R_EVER	Proportion evergreen forest in riparian zone	%
R_MIXED	Proportion mixed forest in riparian zone	%

2.3 Analytical Methods

2.3.1 Partial Least Squares Path Modeling

PLS path modeling is a sophisticated technique for estimating intricate causal relationships within path models that incorporate latent variables (LV; Wold, 1966, 1980). In a PLS model, the inner model consists of latent variables and their connecting paths, while the outer model comprises measured variables (MV; Henseler et al., 2016; see Eq. 3). Within the inner model, path coefficients (pc) quantify the relationships between LVs, whereas in the outer model, the associations between LVs and MVs are represented by weights (W; Hair et al., 2014). Each path coefficient represents the impact of independent variables (i.e., exogenous or 'start of path') on dependent latent variables (i.e., endogenous or 'end of path'). The estimated score of an endogenous latent variable (e.g., $LV_{p,c}$ in Fig. 2; see Eq. 4) is calculated as the weighted sum of all its connected exogenous latent variables, where the Ws are represented by path coefficients:

$$LV_m = \sum_{i=1}^{n} (MV_i * W_i) \quad (3)$$

$$LV_{p,c} = LV_{m,a} * \beta_{ac} + LV_{m,b} * \beta_{bc} \quad (4)$$

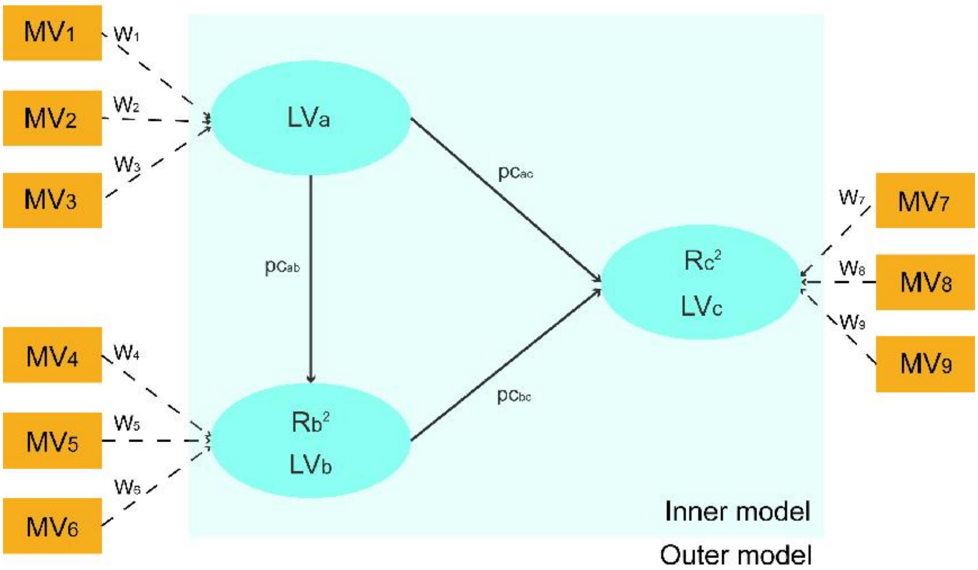

Fig. 2. Partial least squares path model used.

The PLS algorithm can produce either formative of reflexive models. Reflexive models feature paths that originate from LV and terminate at MV, while the arrow directions are reversed in formative models. In reflexive models, measured variables are considered as effects of latent variables, while they are viewed as causes in formative models (Boccuzzo and Fordellone, 2015). In our research, PLS was used as formative model because we assumed all the latent variables determined the measured variables.

We used the coefficient of determination (R^2) for LVs and the Goodness of Fit (GoF) index of the whole model to evaluate the model performance, which serves as a pseudo GoF measure to account for the quality of both the measurement and structural models in evaluating the overall model performance. In a PLS model, R^2 represents the percentage of variance in the dependent variable that is explained by the predicting constructs (Oliveira et al., 2019). Generally, the model performance can be classified into three levels: R^2 <= 0.2 - low, 0.2 < R^2 < 0.6 - moderate, R^2 >= 0.6 - high.

2.3.2 Multiple Linear Regression Models and Post-Hoc Analysis of the Interaction Effect

We applied multiple linear regression to explore the relationship between land cover, soil, slope, daily climate, and TP. The TP value was log-transformed to approximate a normal distribution. We added interaction terms by multiplying two independent variables (Ponce-Palafox et al., 2019): land cover-slope interaction and land cover-soil interaction. To control the number of independent variables and address the multicollinearity issues, we performed least absolute shrinkage and selection operator (LASSO) regression for each model to select the important main effects variables. This is a regression analysis method that performs both variable selection and regularization, which can enhance the prediction accuracy and interpretability of the regression models. LASSO model selection resulted in the following formula for the linear regression model**,** where Y is the dependent variable (TP), and b_i represents the constant and the coefficient of different independent variables. T, P, O, D, F, C, S, CL and SA represent the TMEAN, PPT, DEV_OPEN, DEV, FOREST, CROP, SLOPE, CLAY and SAND, respectively. Table 1 describes the variable in detail. The significant level of regression was set as 0.05:

$$Y = b_0 + b_1T + b_2P + b_3O + b_4D + b_5F + b_6C + b_7S + b_8CL + b_9SA + b_{10}(D*S) + b_{11}(C*S) + b_{12}(O*CL) + b_{13}(O*SA) + b_{14}(C*CL) + b_{15}(C*SA) + \varepsilon \quad (5)$$

To evaluate whether adding interaction variables can significantly improve model performance, we used R^2 and Akaike information criterion (AIC) to compare Eq. 5 and model without interaction variables. Because the number of independent variables in these two models differ, it is not appropriate to use only R^2 to compare model performance. AIC is a proven method for model evaluation with the criteria of the number of independent variables and the maximum likelihood estimate of the model. The best-fit model according to AIC is the one that explains the largest variance with the least independent variables. When models are nested and the sample sizes of models are consistent, the model with the smallest AIC value is preferred.

In post-hoc analysis, we used perspective plots to investigate the significant interaction effects in the regression models. Perspective plots are particularly useful for exploring complex interactions, finding optimal solutions, and identifying trends or patterns in data. The perspective plot can draw a contour graph that explores the relationship between several independent variables and the dependent variable. According to the contour graph of two independent variables, we can then identify the joint effect of them and how the effect of one variable changes with different values of the other variable.

Chapter 3: Results

3.1 Spatial Distribution of Key Variables

The study site and season were characterized by mild climate and favorable ecological conditions. The site experienced relatively cool temperatures, with 22℃ as the average highest monthly temperature. Precipitation distribution varied among different sampling sites and days, ranging from 0 to 46.20mm of daily precipitation. The maximum Rx1day was 120.82mm, with an average value of 32.82mm, indicating the relative wet condition of the sampling season. The average forest land cover percentage was 37.8%, with notably high forest coverage in Southeast Lake Ontario, Susquehanna, Allegheny subregions (HUC 4), and areas around Lake Michigan (see Fig. 3). The major human disturbance was agriculture development, with a 26.7% average crop coverage. The average developed/urban area was only 5%, which would not likely cause stream degradation. Riparian quality was generally good in the study area, with an average QR of 0.59 and an average 0.47 QRVeg. The riparian forest predominantly consisted of deciduous trees (25.6% average coverage). We also found the spatially clustering effect of riparian quality was weak and not correlated with watershed forest coverage. For example, sites in proximity to Lake Michigan and Lake Huron had high forest percentages but low riparian quality.

Overall, the study area exhibited satisfactory conditions for both water quality and fish diversity. Fish diversity was higher near Lake Superior and Lake Michigan, including Northeastern Lake Huron, Northeastern Lake Michigan, and Northeastern Lake Michigan subregions (HUC4), where forest dominated the watershed landscape. However, some watersheds in east Lake Ontario and Lake Erie had low fish diversity, such as the

Southeastern Lake Ontario and the Allegheny subregion (see Fig. 3). The study area exhibited low nutrient concentration, with an average TP 0.08 mg/l and an average TN of 1.98 mg/l. The highest TP concentrations were observed in the Great Miami subregions and Mississippi Headwaters. The conductivity variation was relatively large, with elevated values in the Southeastern Lake Huron, Southeastern Lake Michigan, and Wabash subregions (see Fig. 3).

Table 2. Summarized statistics for variables used.

Variable	*M*	*SD*	Max	Min
Fish community variables				
Richness	12.87	7.53	38.00	1.00
Diversity	1.67	0.68	3.12	0.00
Water quality variables				
TP	89.21	95.19	659.00	6.47
TN	1.98	2.54	16.21	0.11
PH	7.96	0.49	8.67	5.43
COND	445.71	339.87	2773.60	12.20
WATER_TEM	18.25	5.17	27.90	0.001
Climate variables				
TMEAN	19.90	4.14	28.27	7.37
PPT	2.59	6.12	46.20	0.00
W_MTEM	22.02	1.76	26.62	18.54
C_MTEM	-8.13	4.38	1.10	-18.17
Rx1day	32.82	17.31	120.82	8.18
Land cover variables				
DEV_OPEN	4.56	4.16	34.62	0.19
DEV	5.12	8.09	58.60	0.00
FOREST	37.80	27.44	93.33	0.30
CROP	26.72	29.00	94.51	0.00

Slope variables				
SLOPE	4.11	2.55	15.81	0.48
Soil variables				
CLAY	15.91	4.78	39.42	10.00
SAND	40.38	14.29	70.74	16.42
Riparian zone variables				
QR	0.59	0.16	0.99	0.18
QRVeg	0.47	0.20	1.00	0.10
RDIST	0.35	0.23	0.86	0.00
R_DECI	25.60	23.26	88.54	0.02
R_EVER	3.25	7.52	44.93	0.02
R_MIXED	7.28	11.23	65.40	0.05

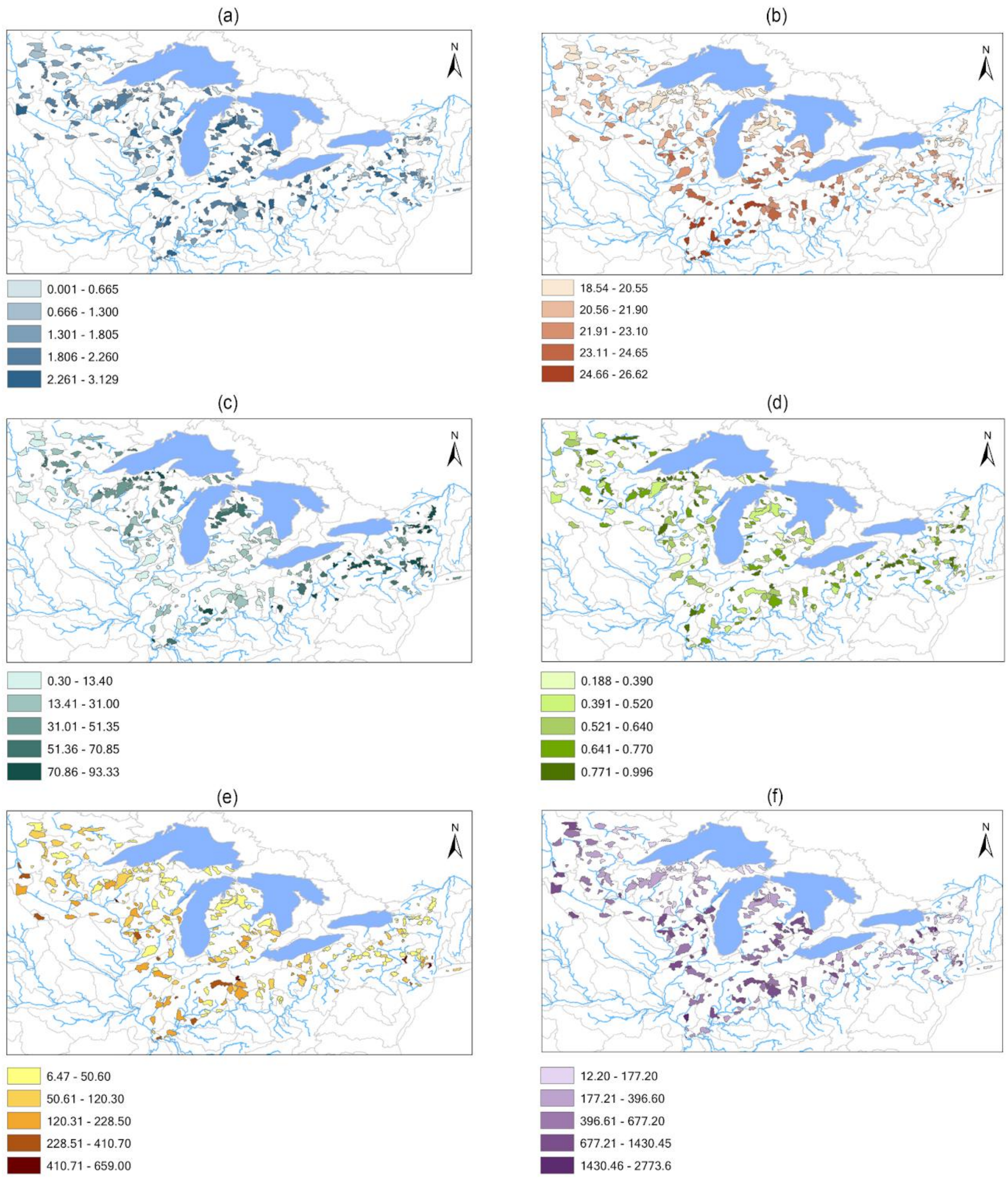

Fig. 3. Spatial distribution of the key variables (a) fish diversity, (b) warmest monthly temperature, (c) forest land cover, (d) riparian quality index, (e) total phosphorus, and (f) conductivity.

3.2 Variable Correlation

The correlation heatmap in Fig. 4 indicates that the variable with the highest correlation to fish diversity was pH (r=0.44), followed by warmest monthly temperature (r=0.32) and water temperature (r=0.27). At the riparian zone scale, fish diversity was surprisingly positively correlated with riparian disturbance score (r=0.26). This might be due to a riparian disturbance leading to high pH and conductivity, which are both increasing fish diversity in the study region. Also, more riparian disturbance was found in warm areas (as indicated by the correlation of 0.43 between riparian disturbance and the warmest monthly temperature) with high fish diversity. Among all watershed characteristics, the percentages of forest, crop, and sand in the soil were the most correlated variable with fish diversity (r=0.22, -0.22, and 0.22, respectively). Fish richness was highly correlated with fish diversity, with the effect of water temperature higher (r=0.38).

Nutrient concentration was associated with both watershed land cover and riparian quality, while watershed land cover's association was stronger. Forest was significantly negatively correlated with TN and TP concentration, while the crop's correlation was significantly positive. Riparian forest coverage was negatively correlated with TN and TP concentration, with deciduous and mixed forests' correlation higher than evergreen forests. In general, the riparian forest coverage was stronger related to TN and TP than the riparian quality and vegetation quality score. Higher forest in the upstream and riparian zone were also associated with lower pH and conductivity. We also found that watersheds with high cropland had lower riparian quality and higher riparian disturbance. The warmest monthly temperature had a significant association with many variables, where warm areas had more disturbed riparian zone, more sandy soil, higher pH, conductivity, and higher nutrient concentration.

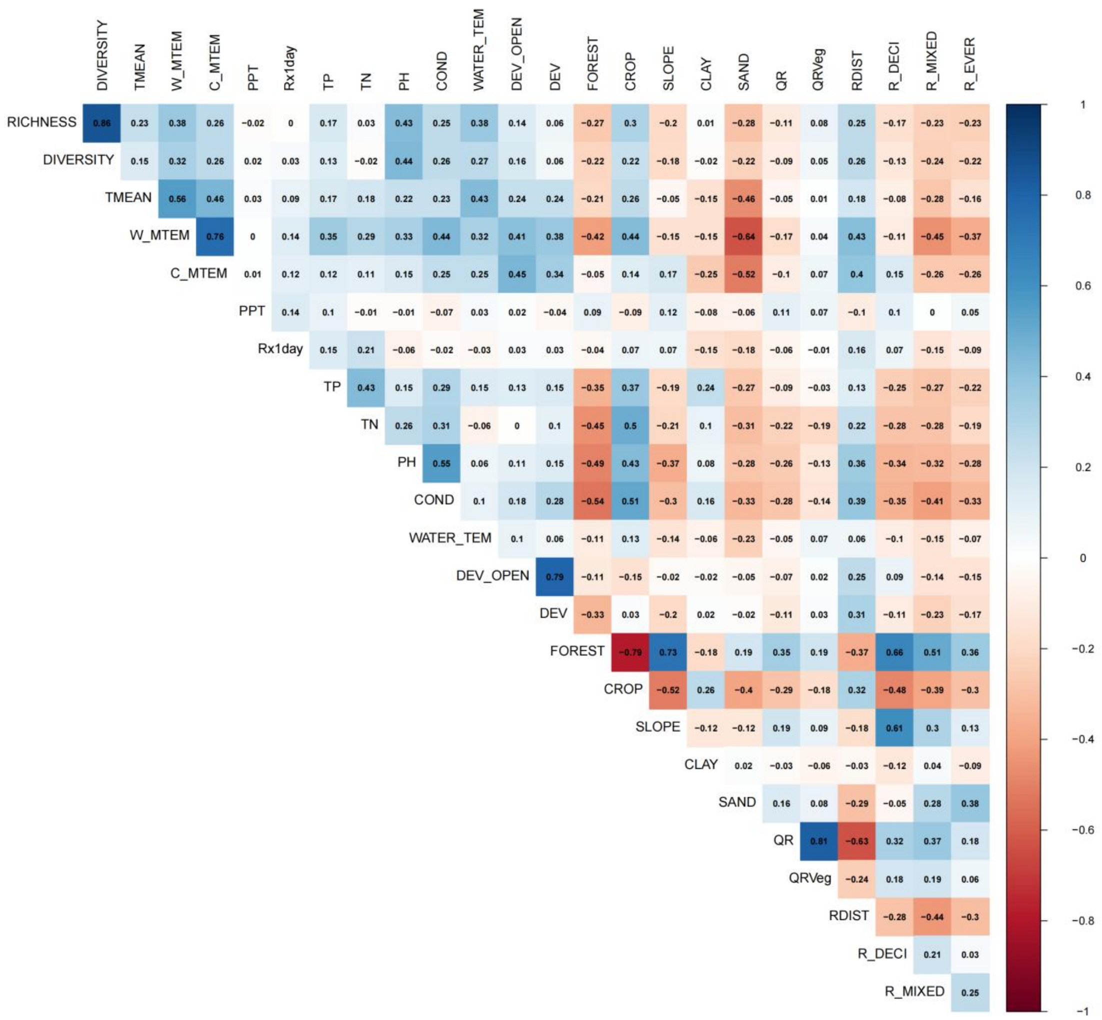

Fig. 4. Correlation map of all variables.

3.3 Pathways of Fish Richness and Diversity

In the PLS model, we linked all the measured variables to six latent variables: watershed development, warm climate, riparian quality, water physiochemistry, eutrophication, and fish diversity. Watershed development was assessed using land use (developed, developed open, forest, crop), slope, soil, and their interactions. According to the PLS results, forest, crop, and their interaction with soil were the most influential factors on the latent variable of watershed development. The warm climate latent variable was quantified using daily temperature, warmest and coldest monthly temperatures, daily precipitation, and Rx1day. The most significant factor for this latent variable was the warmest monthly temperature. Additionally, extreme precipitation as indicated by Rx1day weighed more heavily than daily precipitation. Watershed development and warm climate were exogenous variables that accounted for the variations of other latent variables in the PLS model.

The endogenous latent variables were riparian quality, water physiochemistry, nutrients, and fish diversity. Riparian quality was assessed using different types of riparian forest percentages (i.e., riparian evergreen forest, mixed forest, and deciduous forest percentages), riparian quality index, riparian vegetation index, and riparian disturbance index. The percentages of mixed and deciduous forests in the riparian zone predominantly influenced this latent variable. Water physiochemistry was measured using three critical water quality indicators affecting fish diversity: water temperature, pH, and conductivity, with conductivity and pH weighing more heavily than water temperature. Eutrophication was represented by total nitrogen and total phosphorus concentrations, which had nearly equal weightings. Lastly, fish diversity was evaluated using the fish diversity index and richness index.

In terms of model performance, riparian quality, water physiochemistry, eutrophication, and fish diversity had R^2 values of 0.44, 0.46, 0.31, and 0.25, respectively. As a result, watershed landscape, climate factors, and riparian quality demonstrated moderate predictive power for water quality (Sanchez, 2013), while fish community characteristics were less effectively captured by the measured variables. The relationships between latent variables can be expressed as Equations 6-9.

*riparian quality=-0.58*watershed development-0.14*warm climate (6)*

*eutrophication=0.49*watershed development+0.07*warm climate-0.05*riparian quality (7)*

*water physiochemistry=0.40*watershed development+0.16*warm climate-0.24*riparian quality (8)*

*fish diversity=0.41*water physiochemistry-0.11*eutrophication+0.17*warm climate-0.004*watershed development-0.04*riparian quality (9)*

The above equations indicate that higher fish diversity is associated with higher pH (within the range of 5.43 to 8.67, with an average of 7.96), higher conductivity (within the range of 12.2 to 2773.60, with an average of 445.71), and warmer water temperatures (within the range of 0 to 27.90, with an average of 18.25). Eutrophication contributes to a decrease in fish diversity and richness. Warm and humid climate conditions lead to increased fish diversity and richness. Furthermore, both eutrophication and water physiochemistry are strongly affected by watershed development. Specifically, a higher percentage of cropland and a lower percentage of forest result in higher pH, conductivity, and water temperature. The effect of urban development on nutrients, pH, conductivity, and water temperature is also positive, but not as pronounced as cropland. Riparian quality can reduce eutrophication levels and decrease water temperature, conductivity, and pH. Warm and humid climate conditions increase eutrophication, water temperature, pH, and conductivity.

After substituting the endogenous latent variables (eutrophication, water environment, and riparian quality) in Equations 6-9 on the right-hand side with water physiochemistry and warm climate, we derived a model for fish diversity, eutrophication, and water environment based solely on watershed development and warm climate (Equations 10-12).

$$\mathit{eutrophication} = 0.52\ \mathit{watershed\ development} + 0.08\ \mathit{warm\ climate}\ (10)$$

$$\mathit{water\ environment} = 0.54\ \mathit{watershed\ development} + 0.19\ \mathit{warm\ climate}\ (11)$$

$$\mathit{fish\ diversity} = 0.18\ \mathit{watershed\ development} + 0.07\ \mathit{warm\ climate}\ (12)$$

We found watershed development strongly influenced nutrients and water environment by increasing TP, TN, pH, conductivity, and water temperature. The effect of warm climate on pH, conductivity and water temperature was more pronounced than that on TP and TN. Watershed development caused increasing fish diversity because the disturbance in our study site was only moderate (5% average percentage of development, see Table 2). In general, we concluded that moderate development led to low degree of eutrophication, thus not necessarily decreasing fish diversity.

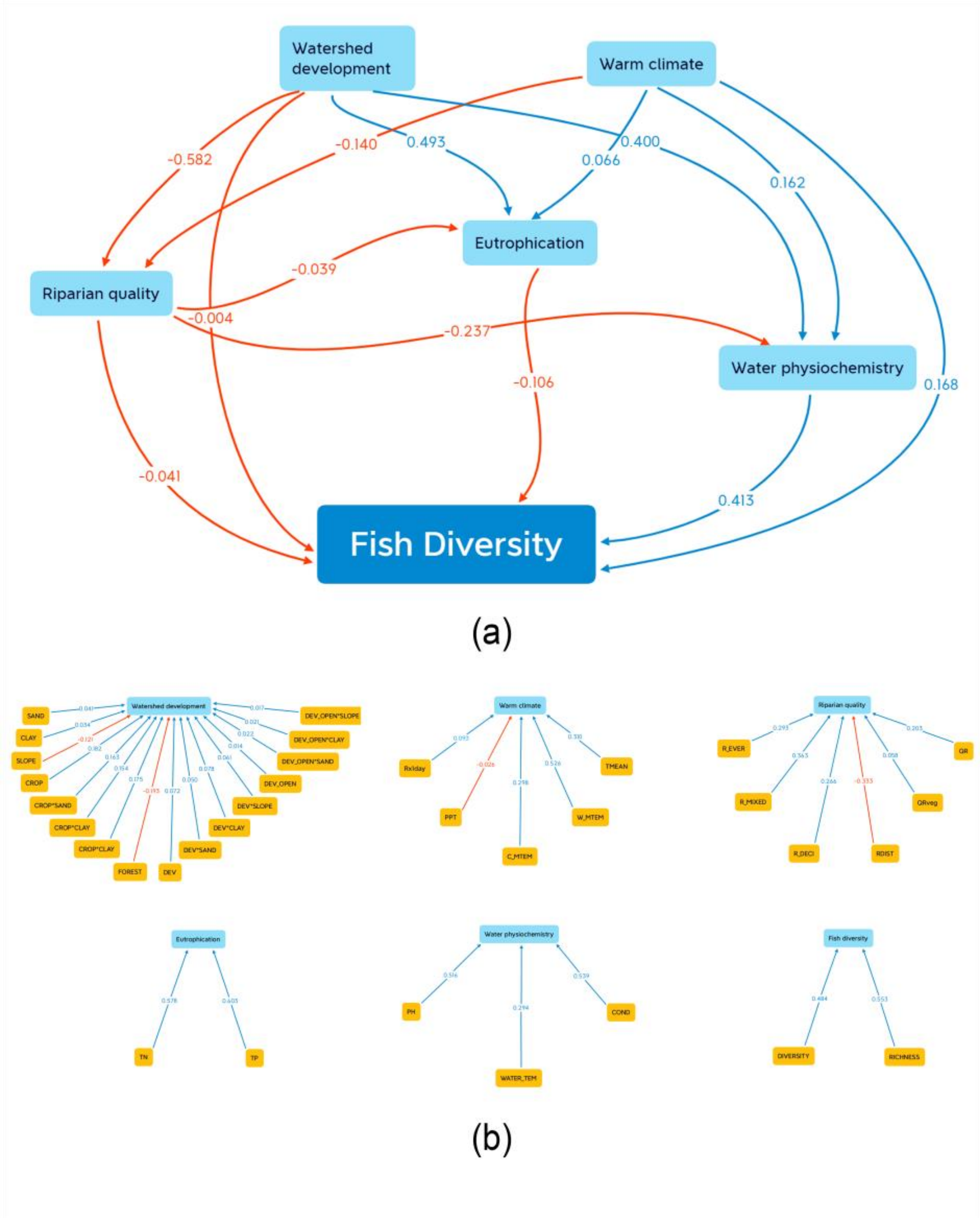

Fig. 5. The outcomes of PLS model. (a) path coefficients between LVs within the inner model, (b) weights of all factors for each LV.

3.4 How Watershed Characteristics Interact to Influence Total Phosphorous

We found adding interaction variables to regression models leads to an increase in R^2 and a decrease in the AIC value, indicating that interaction variables work efficiently with individual variables in explaining TP concentration. Specifically, regression models with only main effects had R^2 of 0.368 and AIC of 734.15; while the R^2 and AIC of regression models with interaction effects were 0.420 and 714.14, respectively (see Table 3).

The effect of crop on TP depended on soil types, while the effect of developed area on TP varied with slope. Specifically, the main effect of crop was negative but not significant. However, CROP-CLAY interaction was positive, indicating the influence of crop on TP gets positive and larger with the increase of clay content in the soil. Also, the CROP-CLAY interaction graphs (see Fig. 6 (a)) indicates that when the proportion of clay in the soil is less than 20%, TP increased slowly with the increase of cropland percentage. However, when the percentage of clay in the soil is larger than 40%, TP increased much more rapidly as the percentage of cropland increased. Developed area had a significantly negative main effect on TP, while the effect changed to positive when the slope gets steeper indicated by the significantly positive DEV-SLOPE interaction (see Table 3). From the DEV-SLOPE interaction graphs (see Fig. 6 (b)), when average slope WAS less than 5%, the increase in the percentage of developed land almost had no impact on TP. However, when average slope was greater than 15%, the percentage of developed land has a strong positive association with TP. Overall, the individual influence of land cover, slope, and soil on TP presented a potentially nonlinear effect due to the interaction with each other. In addition, daily precipitation showed a positive influence on TP, while the effect of forest was negative.

Table 3. Multiple linear regression results with interaction variables.

Predictors	Estimates	CI	*p*
(Intercept)	5.76	4.01 — 7.52	<0.001*
TEMPERATURE	0.01	-0.01 — 0.04	0.244
PRECIPITATION	0.02	0.01 — 0.04	0.002*
DEV_OPEN	-18.99	-44.64 — 6.67	0.146
DEV	-6.69	-10.52 — -2.87	0.001*
FOREST	-1.16	-1.94 — -0.37	0.004*
CROP	-1.28	-2.86 — 0.30	0.112
SLOPE	-0.09	-0.16 — -0.03	0.003*
CLAY	2.27	0.22 — 4.32	0.141
SAND	-1.61	-3.19 — -0.03	0.046*
DEVELOPMENT * SLOPE	2.35	1.06 — 3.63	<0.001*
CROP * SLOPE	0.29	-0.02 — 0.60	0.069
OPEN * CLAY	103.33	-16.90 — 223.56	0.092
OPEN * SAND	7.97	-14.04 — 29.99	0.477
CROP * CLAY	6.26	0.59 — 11.93	0.031*
CROP * SAND	-0.23	-2.94 — 2.48	0.866
Observations	277		
R2/ R2 adjusted	0.449 / 0.420		
AIC	714.135		

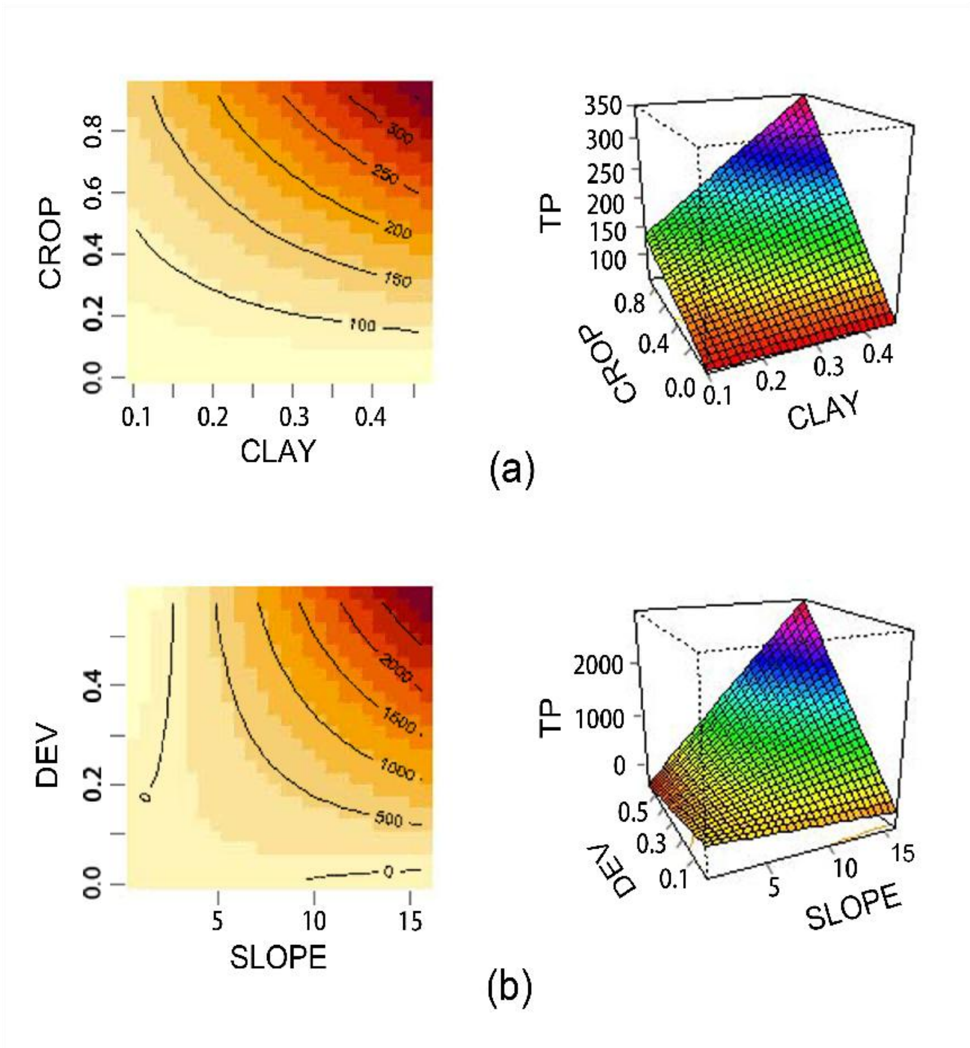

Fig. 6. Contour graph of interaction variables. (a) CROP-CLAY interaction graphs, and (b) DEV-SLOPE interaction.

Chapter 4: Discussion

4.1 The Mechanisms of Fish Richness and Diversity Pathways

We contributed to the existing research on the relationship between watershed development and fish diversity by identifying two distinct pathways– through changing eutrophication levels and through altering other physicochemical indicators such as pH, conductivity, and water temperature. Previous research on the effects of watershed development on fish biodiversity has yielded inconsistent results. For example, many studies found row-crop agricultural had deleterious effects on fish communities primarily because higher loads of fine sediment reduced hatching success (Gido et al. 2010; Sternecker and Geist, 2010). However, other studies have observed relatively high fish community conditions in heavily agricultural areas (comprising over 50% of the basin), which may be attributable to the influence of factors such as nutrient and sediment regulation (Meador and Goldstein, 2003). Our findings indicated that agricultural land use augments nutrient levels, subsequently reducing fish diversity. Concurrently, agriculture also increased conductivity, water temperature, and pH, thereby promoting fish diversity. The combined effects of the two pathways showed an overall positive effect of watershed development on fish diversity. This result supported the previous finding that freshwater fish community was only sensitive to some higher-level threshold of agricultural development (2%-37%, Chen and Older, 2020). The average agricultural land cover of the study site was 26.72%, which might not have caused fish diversity degradation. That said, in our study site, the positive effect of agriculture on fish diversity through changing water physiochemistry outweighed its negative effect through increasing eutrophication, given the relatively low in-stream TP concentration (average 0.08 mg/l). However, it is plausible that with the progression of urbanization, this relationship could be inverted. When watershed development reached certain threshold, the effect of agriculture on eutrophication might surpass the advantageous effects on fish diversity. The other possible reason could be the site climate was cool and humid, where the slightly increasing water temperature caused enhanced biodiversity.

The observed positive correlation between watershed development and fish diversity, as well as the association between riparian disturbance and fish diversity, may be attributed to the relatively low extent of development. This evidence lends support to the well-established "intermediate disturbance hypothesis" (Huston, 2014), which posits that sites with intermediate levels of disturbance may exhibit increased biomass, consequently promoting biodiversity. Specifically, it was found that food availability was highest in streams of open meadow habitat, which represented an intermediate level of disturbance compared to a completed forested stream (Albertson et al. 2017). However, this "intermediate disturbance hypothesis" was ambiguous due to the imprecise definition of "intermediate." In this study, we contribute to the substantiation of this theory by offering empirical evidence suggesting that approximately 5% of urban development may be considered an "intermediate disturbance" for watersheds surrounding the Great Lakes. Also, in addition to food availability, we identified the other possible mechanism of how intermediate disturbed site had high biodiversity—through slightly increasing water temperature, pH, and conductivity.

Existing research has yielded inconsistent conclusions regarding the relative importance of riparian quality and catchment land use in relation to their effects on water quality and fish diversity, where our research supported the significance of catchment land use. Some researchers found measures of water physiochemistry and riparian condition might be better indicators of fish diversity compared to basin wide land use because broader scale land use might not adequately capture local activities affecting fish community (Meador and Goldstein, 2003; Lammert and Allan, 1999). However, some researches highlighted the terrestrial land use and urbanization effects on fish community composition, especially the effects of erosion-prone land use types such as root crop and maize (Bierschenk et al. 2019; Sternecker and Geist, 2010). Our research indicated riparian quality mainly influenced fish diversity by changing water physiochemistry, but this effect was not as strong as the effect of watershed development. Moreover, our findings indicate that an intermediate level of riparian zone disturbance enhances fish diversity, which contradicts numerous studies that have asserted that riparian zones promote fish diversity by reducing nutrient and sediment input into streams (Bierschenk et al. 2019). Riparian quality appeared less critical than watershed land cover and did not exhibit a marked effect on eutrophication, possibly due to the relatively favorable riparian quality in the study area, characterized by an average Riparian Quality Index (QR) of 0.59 and an average deciduous tree cover of 25.6%. Consequently, urban stream syndrome was not evident in the study area.

The warm climate in the study area exhibited a positive impact on fish diversity, which may be attributed to the mild average summer temperature of 18.25°C during the sampling season. The daily temperature throughout this period did not surpass the optimal growth temperature for the majority of species (Jobling, 1981; Tsuchida, 1995). Other research also showed fish migration and diversity were positively related to the water temperature because warmer temperature increased biomass by raising metabolism (Brodersen et al. 2011; Duffy et al. 2016). However, if water temperature keeps rising under climate change, it would decrease fish diversity when it exceeds fish's preferred temperature range and when it starts to cause eutrophication. In addition, extreme precipitation (Rx1day) also had a positive effect on fish diversity in our study. This association may stem from increased streamflow resulting from high precipitation, which in turn generates new habitats for fish and supplies additional food resources (Cheung, 2018; Hollowed et al. 2013). Compared to Rx1day, daily precipitation was a negligible factor for fish diversity. Overall, we identified the pathways that warm weather and high precipitation influenced fish diversity directly and indirectly through changing eutrophication and water physiochemistry. Any future projection of climate change effects on fish community should jointly consider the direct effects of climate change and the indirect consequences mediated by changes in water quality.

4.2 The Mechanisms and Management Implication of How Watershed Characteristics Influenced TP

Both the developed area and slope negatively affected TP when the value of them were small, but the effect changed to positive with the larger values of developed and slope due to the significant positive interaction effects. Generally, steep slopes tended to increase surface runoff volume (Wang et al. 2002; Sueker et al. 2001) and velocities (Lintern et al. 2018; Sliva et al. 2001), which led to a greater chance of mobilization of sediments and pollutions by mass failure or landslides (Bednarik et al. 2010). The observed negative effect of slope in our study may be attributed to the prevalence of cropland and scarcity of forest in flat areas. Previous studies also found that in forest area, the slope had significantly negative correlations with water quality variables, which was because flat areas were cropland and urban land (Yu et al. 2016). Therefore, land cover types and land use activities may outweigh topographic features in their influence on TP concentration (Anbumozhi et al. 2005). Regarding the main effect of developed area, our results were also not consistent with most existing research stating the positive influence of urban area on TP. In the process of urbanization, large vegetative surfaces have been converted into built-up areas, leading to an increase of impervious surfaces (Kim et al. 2017; Li et al. 2018) and therefore increased surface runoff (Li et al. 2019) and deteriorated surface water quality (Owens et al. 2002). The observed inconsistency may be due to the fact that when the percentage of developed area is minimal, the impact of extensive cropland on water quality surpasses that of developed land, thereby exerting a significant positive influence on TP (Yu et al. 2016).

The positive interaction of DEV-SLOPE could be explained by the fact that steeper slopes reduced infiltration and increased surface runoff velocities. According to the results of contour plot of DEV-SLOPE (Fig. 4), we suggested land use planning consider reducing the development intensity in areas exhibiting slopes greater than 15%. Furthermore, we recommend that regulations governing various land uses for TP pollution management be tailored to specific topographical conditions (Anbumozhi et al. 2005).

Among the three types of soil, silt and clay both have high sorption capacity, resulting in their positive association with TP (Lintern et al. 2018). Other research also found a positive correlation between stream TP concentration and the silt and clay content of catchment soils in Finland (Varanka et al. 1989--1999). Different from silt and clay, sand has a higher rate of porosity and holds less water, which leads to a lower nutrient absorption. Consequently, sandy soil improves water quality by reducing nutrient content (Andry et al. 2009), which agreed with our regression model results. The reason why clay soils exacerbated the impact of cropland on TP may be due to the high sorption capacity of clay, causing an increased uptake of phosphorus from fertilizers into the soil and subsequent discharge into adjacent rivers (Johnson et al. 1997). Therefore, we suggested agricultural cultivation should avoid clay-soil areas in land use planning, especially on areas with clay percent larger than 40%. Moreover, although sand had positive influence on water quality, a high percentage of sand could lead to low water-holding capacity, excessive drainage of irrigation, and poor fertilizer use efficiency when planting (Andry et al. 2009). Therefore, the most suitable soil type for planting should comprise a balanced composition (e.g., sandy loam), which accommodates both water quality management and other planting considerations.

4.3 Research Limitations and Outlook

The major limitation of this study is that the quantification of the fish community did not include species-related information. Given the relatively large study area, the same diversity index could represent distinct species distributions across different regions, potentially compromising the internal validity of the PLS model. Environmental factors influence fish species in various ways. For example, research has demonstrated that climate change, characterized by rising and variable temperatures, impacts diverse fish communities more significantly than species-poor communities (Duffy et al. 2016). Also, different fish species occurred at different pH conditions, with the lowest pH ranging from 3.1 to 7.0 (Leuven and Oyen, 1987). Moreover, the species richness was inherently different in regions with varying temperature conditions (Dala-Cort, 2016). Therefore, without accounting for species, our fish diversity and richness index may not be comparable between watersheds. Future research could consider partitioning data according to species distributions and constructing the structural equation models separately. Another related issue was that the model did not consider spatial clustering effects, which could be partially attributed to the spatial pattern of species distribution. More advanced multivariate analysis might be promising to include mixed effects in the PLS model to deal with this issue, such as treating different regions as random effects (Bry et al. 2019).

Due to the data availability issue, the omission of some important variables affecting water quality and fish was another limitation, which could cause incomplete pathways in the PLS model. Stream discharge, for instance, can alter fish diversity by affecting habitat quality and restricting fish movement. Groundwater and baseflow were related to water temperature, dissolved oxygen levels, and nutrient availability (Franssen et al. 2016; Poff et al. 2010; Rolls et al. 2018). However, these hydrological regime-related variables were not available to include in the PLS model. Certain chemical indicators, such as dissolved oxygen and metals, were also absent from the NRSA dataset. Because the study sites had low urban and industrial land uses, we expected metals indicating toxicity conditions to fish would be very low and not cause much bias in the results. Dissolved oxygen was highly correlated with water temperature which was already included in the model. Another omitted variable was the location of dams relative to the sampling sites. Dams could cause habitat fragmentation and prevent fish from accessing important spawning and feeding areas (Liermann et al. 2012). However, the initial quantification of upstream dams was very weakly associated with fish diversity and therefore we removed it from the PLS model. For the next step, we could try quantifying the number of dams within different location buffers relative to the sampling sites to investigate their influence on fish. Furthermore, we also missed some watershed characteristics affecting TP concentration, such as urban growth form, landscape configuration, and land management (Liu et al. 2012; Brabec et al. 2009; Yu et al. 2016). Here we argued these variables were not very important for TP considering the general low urban development intensity in the study area.

Our models were also subject to some multicollinearity and generalizability issues. Despite efforts to mitigate multicollinearity among independent variables through the application of LASSO, the final regression models still exhibited moderate correlations among certain independent variables (e.g., CROP and FOREST, DEV_OPEN and DEV). A similar situation arose when we added interaction variables to the regression models which could led to some biased coefficients in the MLR results. Moreover, the generalization of this research could be limited by the specific context of the study site. Our study sites were characterized by low development intensity and favorable habitat quality. The data collection took place during the summer months in cooler regions, with an average temperature of 19.90 ℃. Consequently, our findings are biased towards favorable environmental conditions and may not be readily applicable to highly developed or warmer regions.

Chapter 5: Conclusion

In this study, we identified pathways through which watershed development, climate, and riparian quality impacted fish richness and diversity by altering water quality indicators. The most crucial pathway involved watershed development, characterized by increased agricultural land use and decreased forest land use, which influenced fish richness and diversity by raising pH, water temperature, conductivity, and nutrient levels. Moderate watershed development, as indicated by the average of 5% developed areas in the study site, resulted in increased fish diversity. Although watershed development negatively affected fish richness and diversity by increasing nutrient concentrations and eutrophication, this pathway was outweighed by the positive effects of increasing pH, temperature, and conductivity. Furthermore, watershed development had a more substantial impact on fish communities than riparian quality. The warmest monthly temperature and Rx1day both positively influenced fish richness and diversity.

This study also revealed how stream TP concentration was affected by the interaction between watershed land cover, slope, and soil. The CROP-CLAY and DEV-SLOPE interactions were both significant factors affecting TP. Specifically, a soil clay content higher than 40% significantly increased the positive effect of cropland on TP, and a slope greater than 15% significantly increased the positive effect of developed areas on TP.

We propose two management suggestions accordingly: (1) Future ecosystem management in the Great Lakes should focus on both watershed management and riparian zone protection to mitigate the negative impact of nutrients on fish diversity. (2) Land use regulation and nonpoint source programs for stream nutrient management should be tailored to regions with different topography and soil textures.

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