Ecological Indicators 154 (2023) 110834

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

# Identifying the critical lakeshore zone to optimize landscape factors for improved lake water quality in a semi-arid region of Northeastern China

Yang Ou [a,c,*], Alain N. Rousseau [b], Baixing Yan [a,c], Yubo Zhang [d], Yuanyuan Sui [d], Hu Cui [a,c]

[a] Key Laboratory of Wetland Ecology and Environment, Northeast Institute of Geography and Agroecology, Chinese Academy of Sciences, Changchun 130102, PR China
[b] Centre Eau Terre Environnement, Institut National de la Recherche Scientifique (INRS-ETE), 490 de la Couronne, Québec, Qc G1K 9A9, Canada
[c] Jilin Provincial Engineering Center of CWs Design in Cold Region & Beautiful Country Construction, Changchun 130102, PR China
[d] Water Conservancy Engineering Construction and Management Station, Songliao River Water Resources Commission of Ministry of Water Resources, Changchun 130021, PR China

ARTICLE INFO

*Keywords:*
Lakeshore
Landscape pattern
Water quality
Spatial scale
Semi-arid region

ABSTRACT

The degradation of water quality and decline in purification capacity of lakeshore zones due to anthropogenic activities and climate change is a growing concern in China. The identification of the critical width of the lakeshore zone remains a challenge due to natural geographic features and pollutant types, that is why a general identification approach has yet to be developed. To facilitate the planning of lakeshore restoration plans, it becomes necessary to conduct studies focusing on the development of relationships between water quality and landscape factors within the lakeshore zone in different regions. In this study, spatio-temporal patterns of water quality of 49 lakes in Western Jilin Province, China, were determined through field monitoring from 2015 to 2019. Multivariate statistical methods were applied to quantitatively identify the relationships between lakes water quality and landscape factors within lakeshore zones of different widths. The results indicated that nitrogen (N) contributed more to eutrophication, while fluoride concentrations were found to be abnormally high. Furthermore, the width of the lakeshore zone was found to have a significant impact on water quality, with a critical width of 150 m having the greatest effect. Cropland and saline land explained almost 50% of the water quality variability throughout different seasons. The results also revealed that dual control of N and phosphorus (P) will be required to prevent eutrophication in the study area. Agricultural activities and severe soil salinization were identified as the main causes of diffuse pollution. The establishment of a width threshold identification framework for lakeshore zones is not only of great significance for development of scientific and acceptable restoration plans for lakeshore vegetation filters in ecologically vulnerable areas of western Jilin, but should also provide an effective and user-friendly tool for implementing diffuse pollution control.

## 1. Introduction

The rapid development of the global economy has led to varying degrees of eutrophication in many lakes worldwide (Nguyen et al., 2022; Tong et al., 2022). High levels of nitrogen (N) and phosphorus (P) in lakes have been shown to alter benthic community composition (Taş et al., 2019; Sitati et al., 2021) and cause irreversible damage to aquatic life, including mortality of some species, thereby negatively affecting the quality and function of the lake environment (Liu et al., 2021). Protection of natural landscapes such as wetlands, forests, and grasslands has been identified as one approach of reducing disturbances induced by human activities, such as expansion of farmland and towns (Jabal et al., 2022). Indeed, according to Foulon et al. (2020) and based on an in-depth review of a dozen case studies, there exist at least four categories of approaches to reduce nutrient loadings and harmful algal blooms (HAB): (i) key regulatory schemes; (ii) incentive-based programs; (iii) risk mitigation approaches; and (iv) outreach, engagement, and educational activities. Protection of natural landscapes most often fall in the category of incentive-based programs accompanied by various educational activities to inform stakeholders and influence their decision-making process. Danz et al. (2007) found that nutrient levels in water were positively correlated with cropland area in the lake basin, while they were negatively correlated with forest area. Houlahan and Findlay (2004) emphasized the important role of woodlands in

* Corresponding author at: Key Laboratory of Wetland Ecology and Environment, Northeast Institute of Geography and Agroecology, Chinese Academy of Sciences, Changchun 130102, PR China.
*E-mail address:* ouyang@iga.ac.cn (Y. Ou).

https://doi.org/10.1016/j.ecolind.2023.110834
Received 16 June 2023; Received in revised form 9 August 2023; Accepted 17 August 2023
Available online 21 August 2023

controlling N and P concentrations in adjacent water bodies. As a transition zone between land and water, lakeshore plays a crucial protective role, but it is strongly impacted by human activities in many regions, resulting in rapid shrinkage and loss of ecological functions (Sawatzky and Fahrig, 2019). It has been widely recognized that restoring the vegetation buffer zone along lakeshores is crucial for reducing agricultural diffuse pollution. However, due to variations in natural geographical features and types of pollutants, the optimal width of the lakeshore buffer zone and the dominant landscape types can vary greatly in different regions. Developing a universal method that integrates field monitoring, remote sensing, and multivariate statistical techniques to identify key parameters for lakeshore restoration plans would be highly valuable for researchers and management personnel. This method would greatly assist local government agencies in formulating lakeshore protection plans, improving the cost-effectiveness of restoration projects, and enhancing the acceptance of such projects by residents.

Preserving natural landscapes around water bodies in agricultural watersheds presents numerous challenges, including the delineation of an appropriate spatial scale for effective conservation projects. Although many scholars have conducted studies on the critical width of riparian/lakeshore zones in different areas, they have not reached a unanimous conclusion. Landscape at different spatial scales, ranging from a 50 m radius around the water body to an entire watershed, can significantly impact water quality, with the intensity of influence often fluctuating depending on geographic features and identification methods (Ou et al., 2016; Sawatzky and Fahrig, 2019). Generally, larger protected areas have a better water purification effect, but they can also occupy large amounts of cropland and incur opportunity costs, causing difficulties for local administrations in developing and implementing conservation plans. Landscape patterns and water quality are intrinsically linked, with many studies revealing interactions between ecological and hydrological processes at different scales (cross-scale interactions) (Peters et al., 2007; Emi Fergus et al., 2011; Birk et al., 2020). However, the relationship between land use and water quality is not always consistent throughout the landscape, making it challenging to select the types of natural landscapes to be protected. For example, in watersheds with a large proportion of agricultural land and intense human activities, wetlands are often negatively correlated with total phosphorus (TP) concentrations and act as sinks (Diebel et al., 2009), whereas in areas with less anthropogenic disturbance, wetlands may cause an increase in TP, transforming them into a source landscape (Devito et al., 2000; Emi Fergus et al., 2011; Ury et al., 2023). The inconsistency of the relationship between landscape and water quality has posed significant challenges in identifying key factors affecting water quality. One of the main reasons for this issue is the insufficient sample size and poor representativeness of the selected river sections or lake samples of existing studies. Additionally, the short duration of monitoring periods has resulted in a lack of continuous long-term water quality data. To enhance the reliability of identifying key influencing factors, it is necessary to expand the scope of the study area, covering larger water bodies and a greater variety of natural and human-induced landscape types. Furthermore, it is important to establish more monitoring stations and conduct continuous monitoring based on local hydrology to identify the spatiotemporal variations of water quality. Close collaboration between researchers and local government agencies remains essential, as it allows for the utilization of existing monitoring data and field sites, enabling reliable identification of key landscape factors influencing water quality at a large scale.

The implementation of buffer zones in the vicinity of water bodies is a highly effective strategy to mitigate agricultural surface pollution, as suggested by several scholars (Polyakov et al., 2005; Ou et al., 2021). Scholars have proposed various buffer widths for riparian zones in different continents, such as North America, where the maximum width required for habitat protection is approximately 100–300 m, followed by 50–100 m for sediment control and bank stabilization, and 10–50 m for achieving water quality goals (Huel, 2000; Lee et al., 2004; McElfish et al., 2008). Similar guidelines for buffer strips are available in Europe, South America, and Australia (Halse and Massenbauer, 2005; Auditors, 2014; Machado and Anderson, 2016). Nonetheless, the optimal width of effective buffer zones to safeguard lake water quality in agricultural watersheds remains unclear, particularly in watersheds with relatively flat topography where identifying the flow direction of surface runoff around lakes becomes challenging. While many studies have focused on the design and evaluation of buffer zone efficiency of rivers or streams, few studies have been conducted on lakeshores (Emi Fergus et al., 2011; Sawatzky and Fahrig, 2019). As a result, the optimal width of riparian buffers vary widely, ranging from 5 to 300 m in different areas (Lee et al., 2004; Rasmussen et al., 2011). Given the difficulty of quantifying the critical width of lakeshore buffers, official guidelines for their design are typically measured in terms of the minimum distance from the water body to cropland (McElfish et al., 2008). However, differences in climate, topography, and human activities make it challenging to generalize buffer strip widths estimated using empirical methods to large scale areas. The critical width of the lakeshore zone could be considered an ecological threshold governing the relationship between landscape features and water quality, but it could be strongly influenced by physiographical features and water quality indicators (Xu et al., 2023). Many threshold phenomena in ecosystems have significant impacts on various ecosystem service functions (Groffman et al., 2006; Mironova et al., 2022). Thus, understanding ecological thresholds and applying them to policy decisions could enhance the efficiency of environmental management. However, incorporating ecological threshold concepts into environmental modelling and management poses several obstacles due to the lack of a generalized approach for identifying thresholds for specific regions, as field monitoring is typically time-consuming and costly (Kelly et al., 2015). Ecological thresholds are critical values or tipping points that can single out a significant change in an ecosystem when a certain characteristic or component reaches a cumulative level of change. Currently, the identification of threshold phenomena in different ecosystems primarily relies on direct monitoring methods. Examples include the minimum vegetation cover required for self-recovery in degraded forest systems, or the nutrient concentration in water bodies that leads to significant changes in benthic macro-invertebrate and aquatic plant community structure. These changes in ecosystems can be relatively and easily quantified. However, quantifying the overall impact of different riparian or lakeshore landscapes on water quality is more challenging, and this is where identifying critical width thresholds becomes difficult. To address this challenge, it is possible to overcome this bottleneck by utilizing gradient analysis statistical methods to quantitatively estimate the effects of multiple independent variables on multiple response variables and combining it with logistic regression growth models. This approach holds promise for ultimately determining critical widths in lakeshore landscapes in different study areas.

The western region of Jilin boasts a substantial number of shallow lakes, which provide habitat for numerous rare animals and exhibit a high level of biodiversity, thus playing a crucial role in maintaining ecosystem security in Northeast China (Gu et al., 2022). Unfortunately, since the 1970s, these lakes have been shrinking due to droughts and construction of upstream irrigation facilities, leading to a reduction in the natural water supply. In 2014, wetlands in the region covered an area of approximately 2441 $km^2$, a mere 43.6% of what they were in the 1950s. Additionally, droughts have caused severe soil salinization in western Jilin, resulting in a significant amount of land becoming barren, making it one of the three major saline areas in the world with an extremely fragile ecosystem (Chang et al., 2022). The safeguard of the water environment in western Jilin, an important ecological barrier in the Northeast China, is paramount. However, recent expansion of cultivated land combined with the adverse effects of climate droughts have caused severe losses of lakeshore vegetation filter strips which have increased the threat of agricultural diffuse pollution to the ecological safety of lakes. Current research has mainly focused on nutrient transformation mechanisms and their impacts on planktonic organisms within important lakes of this region (Liu et al., 2021), yet the development of scientifically efficient restoration plans for lakeshore zones remains an urgent issue that needs to be addressed. The shallow water depth and high salinity of lakes in this region makes it difficult to select physicochemical indicators that could effectively characterize water quality changes in this type of lakes. Moreover, the extensive distribution of saline-alkali land must be considered when identifying landscape indicators. In quantifying the overall impact of landscape characteristics on lake water quality within different lakeshore widths, accurately discerning and integrating the results obtained from various statistical methods becomes crucial. Therefore, the objective of this study was to validate the following hypotheses: (i) significant spatiotemporal variations exist in lake water quality of western Jilin; (ii) landscape features within lakeshore zones are remarkably related to lake water quality; (iii) there is a non-linear relationship (threshold) between the width of the lakeshore zone and the ensuing effect of landscape features on lake water quality.

The identification of spatio-temporal variations in nutrient concentrations in many shallow water bodies of study area will provide important data for prioritizing the control of N and P pollution in eutrophic lakes of China. The determination of the critical width of the lakeshore zone will have major implications for the development of scientifically and acceptable restoration plans for ecologically vulnerable areas of western Jilin, as well as provide a quantitative basis for future assessments of restoration effectiveness of lakeshore vegetation filter strips. The establishment of a framework for identifying the critical width threshold will not only provide an effective tool for diffuse pollution control in different countries and regions, but also further promote the development of quantitative identification of landscape-water quality relationships.

## 2. Material and methods

### 2.1. Study area

The study area, situated in the western part of the Jilin Province in Northeastern China, spans an area of approximately 47,011 km$^2$ (Fig. 1). Four national nature reserves, namely those of Xianghai, Momog, Chagan Lake, and Baluo Lake, have been established in the region, with Xianghai and Momog being designated as internationally important wetland sites. The lakes in the area are primarily recharged by rainfall-runoff processes occurring within their catchments, owing to droughts and the impact of upstream dams, and are therefore characterized as isolated hydrological systems. Despite the low hydrological connectivity of the study area, the ecological degradation has provided a relatively ideal setting for investigating the relationship between landscape and water quality. The region experiences a continental climate, with an average temperature of 4.6 °C, precipitation ranging from 400 to 500 mm, and actual evaporation of 1700–1900 mm (Wang et al., 2009). Precipitation is unevenly distributed in space and time due to the region's geographical location and topography, with the months of June, July, and August accounting for 71.2% of annual precipitation. The terrain is flat and low-lying, with elevations ranging from 100 to 600 m. Soil types are diverse, with black calcareous, meadow, and saline soils being the most prevalent. The region has a low per capita income, with over 60% of the population engaged in agriculture, particularly planting and animal husbandry, with corn and rice being the primary food crops. Cropland (50.81%) and bare land (17.98%) are the primary land use types in the study area.

### 2.2. Lake water quality monitoring data

In the study area, a total of 203 lakes were assessed based on their surface area, spatial location, and hydrological characteristics, with 49 lakes being selected as monitoring objects (Table 1). Lakes with a surface area of less than 10 ha or those deemed seasonal were excluded from the study. Samples were collected at a depth of 0.5 m in the geometric center of the lakes. In cases where the surface area of the studied lakes exceeded 500 ha, the sampling sites were increased based on local conditions. Ultimately, a total of 68 sites were selected and visited between 2015 and 2019.

The water sampling period was divided into a rainy season (i.e., June to August) and a dry season (i.e., April to May and September to October), based on the amount of local rainfall. During the rainy season,

**Table 1**
The morphometric and anthropogenic characteristics of the studied lakes in 2010–2019 (n = 49).

| | Surface area (km$^2$) | Average depth (m) | Volume (10$^4$ m$^3$) | Watershed area (km$^2$) | Population (people/km$^2$) |
|---|---|---|---|---|---|
| Average | 21.6 | 2.2 | 2114 | 71.3 | 18.8 |
| Median | 4.2 | 1.9 | 275 | 24.6 | 17.1 |
| Minmum | 0.1 | 0.6 | 3 | 0.4 | 1.3 |
| Maxmum | 307.5 | 6.3 | 42,600 | 1070.7 | 37.1 |

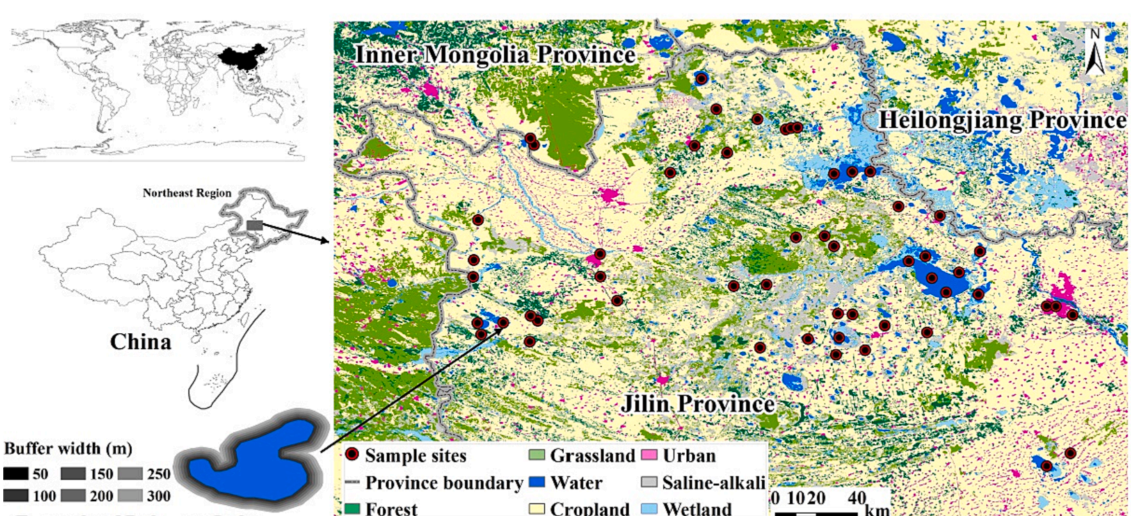


**Fig. 1.** Sampling sites nearby the 49 lakes of the Western Jilin Province, China, and the six lakeshore buffer scales (example of Dabupao lake).

water sampling was conducted once every 10 days, while during the dry season, it was conducted once every half a month. The study area is characterized by developed agriculture and livestock husbandry, and long-term climate drought, which informed the selection of five water quality parameters to represent the status of the lakes: total phosphorus (TP), total nitrogen (TN), dissolved oxygen (DO), total organic carbon (TOC), and fluoride ($F^-$). TN/TP is an important parameter for evaluating the eutrophication status of lakes, and was therefore retained as a crucial water quality parameter (Qin et al., 2020; Tong et al., 2020). Although fluoride is not regularly monitored, its concentration in the lake water was high due to the continuous drought in the study area, and therefore, F- was continuously monitored in this study (Zhang et al., 2007). DO was measured on-site using HQ30d portable water quality instruments (HACH, USA), while other parameters were determined in the laboratory, with water samples being carried in cold storage in accordance with national standard methods.

### 2.3. Landscape features

The present study utilized a fusion of Landsat-8 and Sentinel-2 images to obtain land cover data with high spatial resolution (10 m). Based on geographical characteristics and research objectives, the image was classified into seven distinct land cover types, including cropland, grassland, forest, wetland, water, urban, and saline ground. The accuracy of the classification was assessed and found to be 96.2%. Notably, the presence of bare land in the study area was primarily attributed to salinization, and thus, to better reflect the natural environmental characteristics, bare ground was replaced by saline ground in subsequent analyses. The proportions of different land cover types within the lakeshore zones were used to represent the composition of the landscape, while the configuration metrics were used to quantitatively describe the spatial pattern of the landscape.

Diffuse pollution is an ecological process of pollutant migration from soil to water bodies, and the relationship between pattern and process is a crucial topic in landscape ecology (Wu and Lu, 2019). The pollutant load is determined by the landscape composition, and the spatial distribution pattern of source and sink landscapes, such as cropland and wetland, respectively, significantly affects surface runoff and sediment transport, ultimately impacting the discharge of pollutants to surface water (Ustaoğlu and Tepe, 2019). To explore the relationship between landscape and water quality, many scholars have proposed introducing landscape pattern indices (Li et al., 2018; Zhang et al., 2021; Cheng et al., 2023). However, the complex design of many landscape indices makes it difficult to reasonably explain their impact on water quality. To address this issue, this study selected relatively simple patch density (*PD*), edge density (*ED*), and contagion (*CONTAG*) as representative variables and calculated them using Fragstat4.0 software. *PD* and *ED* represent the number of landscape patches and the perimeter of all patches within a unit area, respectively, and mainly reflect the degree of regional heterogeneity. The estimation of patch and edge densities is as follows:

$$PD = \frac{N}{A} \tag{1}$$

where $N$ is total number of patches in landscape and $A$ is total landscape area ($km^2$).

$$ED = \frac{E}{A} \tag{2}$$

where $E$ is total length (m) of edge in landscape and $A$ is the total landscape area (ha).

*CONTAG* represents the aggregation degree or extension trend of different types of patches. The better the connectivity between patches, the greater the value; otherwise, the higher the degree of fragmentation of the landscape. The contagion can be calculated as follows:

$$CONTAG = \left[1 + \frac{\sum_{i=1}^{m}\sum_{k=1}^{m}\left[P_i\left(\frac{g_{ik}}{\sum_{k=1}^{m} g_{ik}}\right)\right]\left[\ln\left(P_i\left(\frac{g_{ik}}{\sum_{k=1}^{m} g_{ik}}\right)\right)\right]}{2\ln(m)}\right] \times 100 \tag{3}$$

where $P_i$ is the proportion of the landscape occupied by patch type (class) $i$, $g_{ik}$ is the number of adjacencies (joints) between pixels of patch types (classes) $i$ and $k$ based on the double-count method, $m$ is number of patch types (classes) present in the landscape, including the landscape border if present.

In this study, polygonal vector buffers with varying widths were generated using lake water surface edges sourced from the National Geomatics Center of China. The resultant polygons were subsequently overlaid onto the land cover, facilitating the extraction of raster landscape data (10 m) from each lakeshore zone. The selection of buffer widths (50 m, 100 m, 150 m, 200 m, 250 m and 300 m) was based on the pixel size (10 m) of the land cover, as illustrated in Fig. 1.

### 2.4. Statistical analyses

The present study used statistical methods to analyze the relationship between water quality and landscape characteristics. Initially, the Kolmogorov-Smirnov (K-S) test was used to assess the distribution of water quality and landscape data. In cases where the data did not conform to a normal distribution, a logarithmic transformation was applied to normalize them. Subsequently, the one-way ANOVA test was employed to determine whether there were significant differences in water quality across seasons. To identify correlations between water quality (response variables) and landscape characteristics (predictive variables), two methods were considered: Pearson correlation analysis and multiple linear regression (MLR). The Pearson correlation coefficient (R) was used to detect statistically significant covariate trends between a single landscape factor and a single water quality indicator. However, this method was primarily used for preliminary screening of landscape variables, as the relationship detected by R may not necessarily exist in the real world. In contrast, MLR does not only characterize the impact of multiple landscape factors on a single water quality indicator under the constraint of the coefficient of determination ($R^2$), but also provides the direction of correlation. Its reliability has been confirmed by several studies and is widely used in this field. Accordingly, a total of twelve MLR models were conducted in this study, categorized according to water quality indicators and seasons.

Canonical correspondence analysis (CCA), redundancy analysis (RDA), and structural equation modeling (SEM) were considered as potential methods for analysis. CCA and RDA, both belonging to the direct gradient analysis technique, involve Principal Component Analysis (PCA) of the fitted value matrix of multivariate MLRs between the response variable matrix and explanatory variables. While CCA is suitable for normal distribution datasets, RDA is applicable to a wider range of datasets. On the other hand, SEM is a set of statistical methods that integrate Factor Analysis (FA), ANOVA, and MLR. This technique focuses on the influence of covariance of explanatory variables on their ability to explain the response variable. As this study aimed to identify the differences in explanatory power of each landscape variable, the effects of covariation had to be excluded. Moreover, the landscape dataset distribution was not normally distributed, so RDA was chosen to identify the impacts of landscape variables on multiple water quality indicators. The sorting axes of RDA are linear combinations of the predictive variables (landscape factors), and the first two axes with higher eigenvalues are usually selected to explain the response variables (water quality indicators). RDA was conducted separately for each lakeshore width, and Monte Carlo permutation tests reduced the number of model tests. To identify the significance ($p < 0.05$) of the first canonical axis and of all canonical axes together, 499 unrestricted permutations were applied. The variation proportion ($R^2$) of overall water quality (response variables) considering all landscape variables (predictive variables) was calculated using the equation used in RDA. (Ou et al., 2016):

$$R^2 = \frac{trace(\hat{Y}'\hat{Y})}{trace(Y'_{cent}Y_{cent})} = 1 - \frac{trace[(Y_{cent} - \hat{Y})(Y_{cent} - \hat{Y})]}{trace(Y'_{cent}Y_{cent})} \quad (4)$$

where $\hat{Y} = X(X'X)^{-1}X'Y_{cent}$ represents the matrix of predicted values; Y, the multiple response variables and X, the multiple predictive variables. $Y_{cent}$ = (I-P)Y represents the matrix Y centered by column means; I, a (n × n) identity matrix and P, a (n × n) matrix with all elements = 1/n; n is the number of sample sites.

Before applying MLR and RDA, the variance inflation factors (VIF < 10) for each of the landscape variables were pre-tested. The Kolmogorov-Smirnov (K-S) test, ANOVA, and MLR were assessed using SPSS22.0 (IBM Company, USA), while RDA was performed using CANOCO 4.5 (Microcomputer Power, USA). Box plots and line plots were generated using Origin 2016.

## 3. Results and discussion

### 3.1. Spatio-temporal variations of water quality

Between 2015 and 2019, a survey of 49 lakes in Western Jilin, China, revealed mean concentrations of TN, TP, DO, F, and TOC of 1.9 mg/L, 0.28 mg/L, 6.4 mg/L, 3.8 mg/L, and 14.1 mg/L, respectively. The Chinese environmental quality standards for surface waters classify TN concentrations exceeding 1 mg/L as polluted, and 21 of the 49 surveyed lakes exceeded this limit, while 25 exceeded the Class IV limit of 1.5 mg/L. TP concentrations in 13 lakes exceeded the Class III limit of 0.05 mg/L, and 27 lakes exceeded the Class IV limit of 0.1 mg/L. The average TP concentration (approximately 0.28 mg/L) in the surveyed lakes was approximately 10 times higher than the national average (0.03 mg/L) (Tong et al., 2017) and higher than that of Europe and the USA (approximately 0.02 to 0.04 mg/L) (Stoddard et al., 2016). The TN concentration was also higher than the national average and that of Europe and the USA (Stoddard et al., 2016). The TN/TP mass ratio of the surveyed lakes (17.3) (Fig. 2C) was much lower than the national (31.6) and European lake levels (31) but like that of the USA (Tong et al., 2020). Field monitoring and hydrological simulations indicated that most lakes in Western Jilin were in a moderate to severe eutrophication state (Liu et al., 2021, and prevention HAB was advocated for environmental management. The N:P ratio was identified as a stoichiometric indicator closely related to algal growth, and identifying its main drivers can control HABs and support the development of effective nutrient management goals (Tsegaye et al., 2006).

Multiple studies have examined the factors influencing the spatial variation of the N:P ratio in different regions. Cropland has been

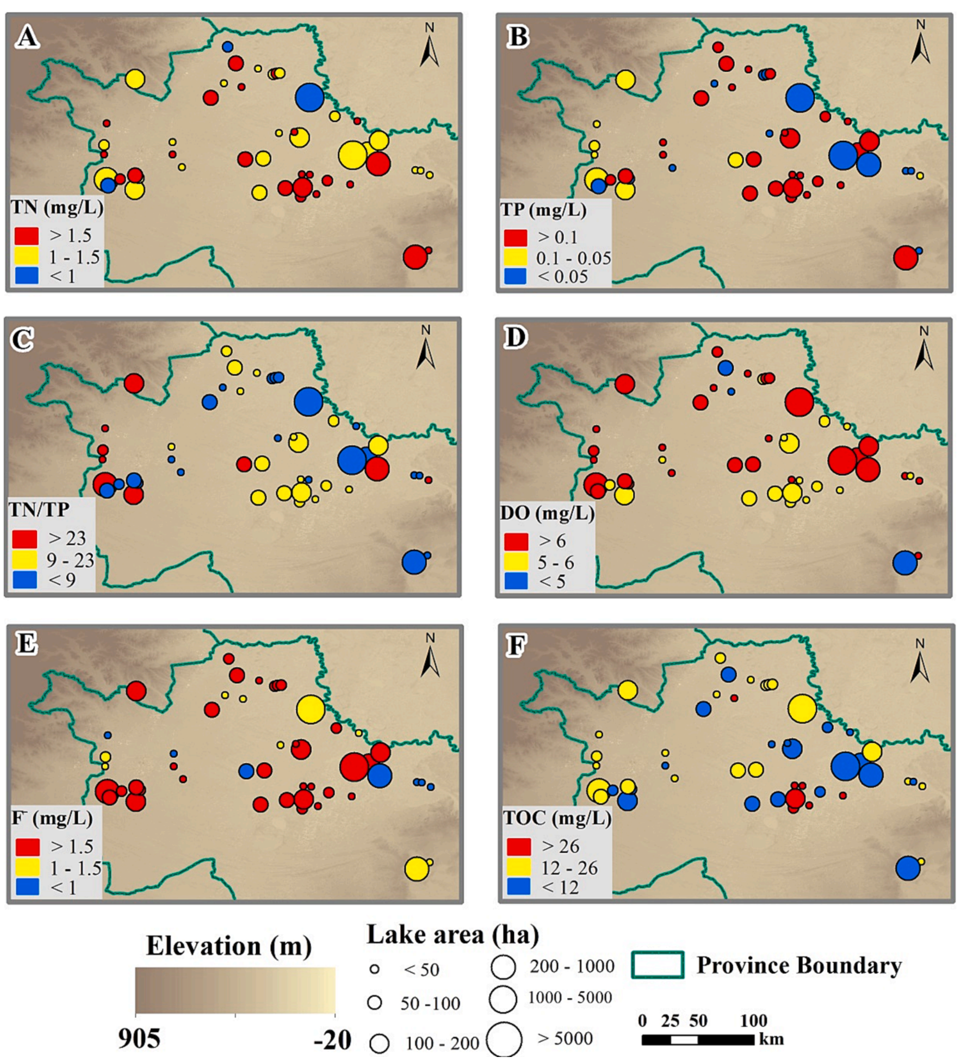


**Fig. 2.** Annual average of TN concentrations (A) and TP concentrations (B), TN/TP mass ratios (C), DO concentrations (D) and $F^-$ concentrations (E), and TOC concentrations (F) in the surveyed lakes in the Western Jilin Province, China.

identified as a significant factor in North America and Europe, while the geometric characteristics of lakes have played a more prominent role in Central and Southern China (Manning et al., 2020; Tong et al., 2022). The TN/TP mass ratio has been commonly used to determine the limiting nutrient for algal growth, where a ratio less than 9 suggests N limitation, and a ratio greater than 23 indicates P limitation (Tong et al., 2020). The analysis of 49 surveyed lakes in the study area revealed that 17 had TN/TP mass ratios less than 9, indicating a higher level of TP enrichment in these lakes. This finding is consistent with a hydrodynamic-ecological modeling assessment that N has a more significant impact on phytoplankton community structure than P in the region (Liu et al., 2021). The prioritization of N or P control in global lake eutrophication management strategies is still a subject of significant debate due to the influence of natural geographical features and variations in lake geomorphology. Generally, N has a larger effect on growth and reproduction of phytoplankton, while P is closely associated with benthic plants and cyanobacteria. Consequently, N limitation is more likely to occur in shallow lakes, whereas P limitation is more prominent in others. Indeed, a global study conducted by Qin et al. (2020) emphasized the prevalence of P limitation in lakes and suggested that N limitation is more common in shallow lakes. The control strategies for eutrophication and HABs should be determined by the hydrodynamic characteristics of the lakes. The findings of this study further validate the view that eutrophication in shallow lakes is nitrogen-limited, providing data support for environmental protection of small lakes. It also indicates that a dual control strategy of N and P must be adopted in the future for Chinese lakes to effectively improve environmental health of surface waters.

The measurement of DO content in water bodies is an essential indicator of water quality. It provides a direct correlation to the level of eutrophication in lakes and has a significant influence on the growth of plankton and benthic invertebrates (Klose et al., 2012; Taş et al., 2019). However, DO level is not solely dependent on the metabolic rate of the water ecosystem, but also on various factors such as water temperature, atmospheric gas exchange, physicochemical reactions, and oxygen-consuming substances transported by surface water and groundwater (Hanson et al., 2006). The expansion of agricultural and urban land has been found to increase flooding frequency, destroy riparian vegetation, reduce shade, and increase water temperature, as well as discharges of sediments, nutrients, and organic matter into water bodies (Allan, 2004; Sawatzky and Fahrig, 2019). Over the past two decades, numerous studies have identified significant correlations between DO concentrations and multi-scale landscape variables in North America (Boeder and Chang, 2008), East Asia (Shi et al., 2017; Zhang et al., 2019), and Africa (Sitati et al., 2021). In this study, DO levels of surveyed lakes were found to be mostly rich, with only three lakes having levels below the surface water Class III limit (5 mg/L), as shown in Fig. 2D. The shallow depths of the surveyed lakes, with the largest of the 49 lakes having an average depth of no more than 2.5 m, was identified as a significant factor.

Shallow lakes are strongly disturbed by wind and waves, resulting in a high degree of reoxygenation, ensuring that both the surface and bottom layers of the lakes have sufficient DO all year round. The oxidized state of the surveyed lake sediments is attributed to the combination of trivalent iron ions ($Fe^{3+}$) with P, leading to the formation of easily depositable iron phosphate ($FePO_4$), which suppresses the release of P at the soil–water interface and results in the P enrichment in the lakes. The study further reveals that the $F^-$ concentrations in 42 surveyed lakes exceed the surface water Class III limit (1 mg/L) (Fig. 2E), with the highest value being 15 times greater than the Class IV limit (1.5 mg/L), indicating serious $F^-$pollution that may be linked to the unique natural geographic conditions of the study area. The persistent drought and strong evaporation in the region have led to soil salt concentrations of more than 0.5%, resulting in severe salinization (Zhang et al., 2007). This has caused a significant amount of $F^-$ to be adsorbed by soil colloids and enriched in the soil solution, with an average concentration of soluble fluorine being 2.5 times higher than the national maximum allowable value (GB15618-2008). The current study reports that the national surface water standard for TOC was absent, and only 11 lakes in the country exhibited TOC concentrations (16.2 mg/L) above the national mean (Song et al., 2018), as compared to each other. However, these concentrations were almost twice the global average, as reported by Chen et al. (2015). This disparity can be attributed to the extensive soil salinization in the study area, which has resulted in a significant reduction in soil organic matter content. This, in turn, has led to a decrease in the organic matter load entering the lake with runoff, ultimately resulting in lower TOC concentrations. Nevertheless, the high intensity of agricultural and livestock activities in the region has caused a significant loss of organic matter, leading to significantly higher TOC concentrations in the surveyed lakes as compared to the global level, as reported by Larsen et al. (2011).

Based on the findings of the monthly monitoring data from 2015 to 2019 presented in Fig. 3, significant seasonal variations were observed in the concentrations of TP, DO, $F^-$, and mass ratios of TP/ TN. However, TN and TOC concentrations did not exhibit significant changes. Specifically, the concentrations of TP in 41 of the 49 lakes increased during the rainy season by an average of 57.1% compared to that of the dry season, indicating the occurrence of diffuse pollution linked to rainfall-runoff events that significantly increased P input to water bodies. Although no seasonal difference was observed in the concentration of TN, the TN/ TP ratio during the dry season was significantly higher than that of the rainy season, with an average value greater than 23. Given that P is the limiting factor for algae growth, it was expected to play a significant role in promoting eutrophication. However, the decrease in temperature during the dry season resulted in a negligible influence of P on algae growth, as the probability of eutrophication was extremely low. Moreover, the decrease in temperature led to an increase in DO concentrations in almost all lakes during the dry season, with an average increase of 37.6%. Like TP, the concentration of $F^-$ in 36 lakes increased significantly with the increase in runoff during the rainy season, and the average concentration increased by 38.6%. The concentration of TN was greatly affected by seasons, with little variation, mainly due to the vigorous growth of wetland vegetation in summer and the rapid rise in temperature, significantly reducing TN loads in lakes by increasing microbial biomass and activity (Hansen et al., 2018). During the dry season, although TOC loads in lakes declined with the decrease in runoff, the concentration of TOC did not significantly decrease. This could be attributed to the continuous decomposition and release of organic matter from the substrate induced by the accompanying increase in DO concentration in shallow lakes (Hanson et al., 2006; Maerki et al., 2009), ultimately leading to dynamic equilibrium of the water column TOC concentration.

### 3.2. Land use/land cover distribution

Fig. 4 presented an analysis of land cover within various widths of lakeshore zones, demonstrating that wetland, cropland, and saline-alkali land constitute most of the land cover, accounting for approximately 80% of the total area. The proportion of wetlands decreased by 12.9% as the lakeshore zone width increased from 50 m to 300 m, while cropland increased by 11.64%. However, the proportion of saline-alkali land did not exhibit significant variation. This indicates that human activities (*i.e.*, cropland) intensify as distances from water bodies increase, resulting in a shift from natural to anthropogenic landscapes. Grassland, forest, and urban areas were not significantly impacted by the width of the lakeshore zone, with the proportion fluctuating around 1%. Wetland area decreased rapidly as the lakeshore zone width increased, making grassland a crucial sink landscape. Forest and urban areas were similar in size, accounting for only 5% of the lakeshore zone each. Due to the low proportion of forest within the lakeshore zone, it did not play a significant role in the statistical analysis as a landscape characteristic parameter. However, research has shown that urban areas, despite their low proportion within a watershed or riparian zone, have a high

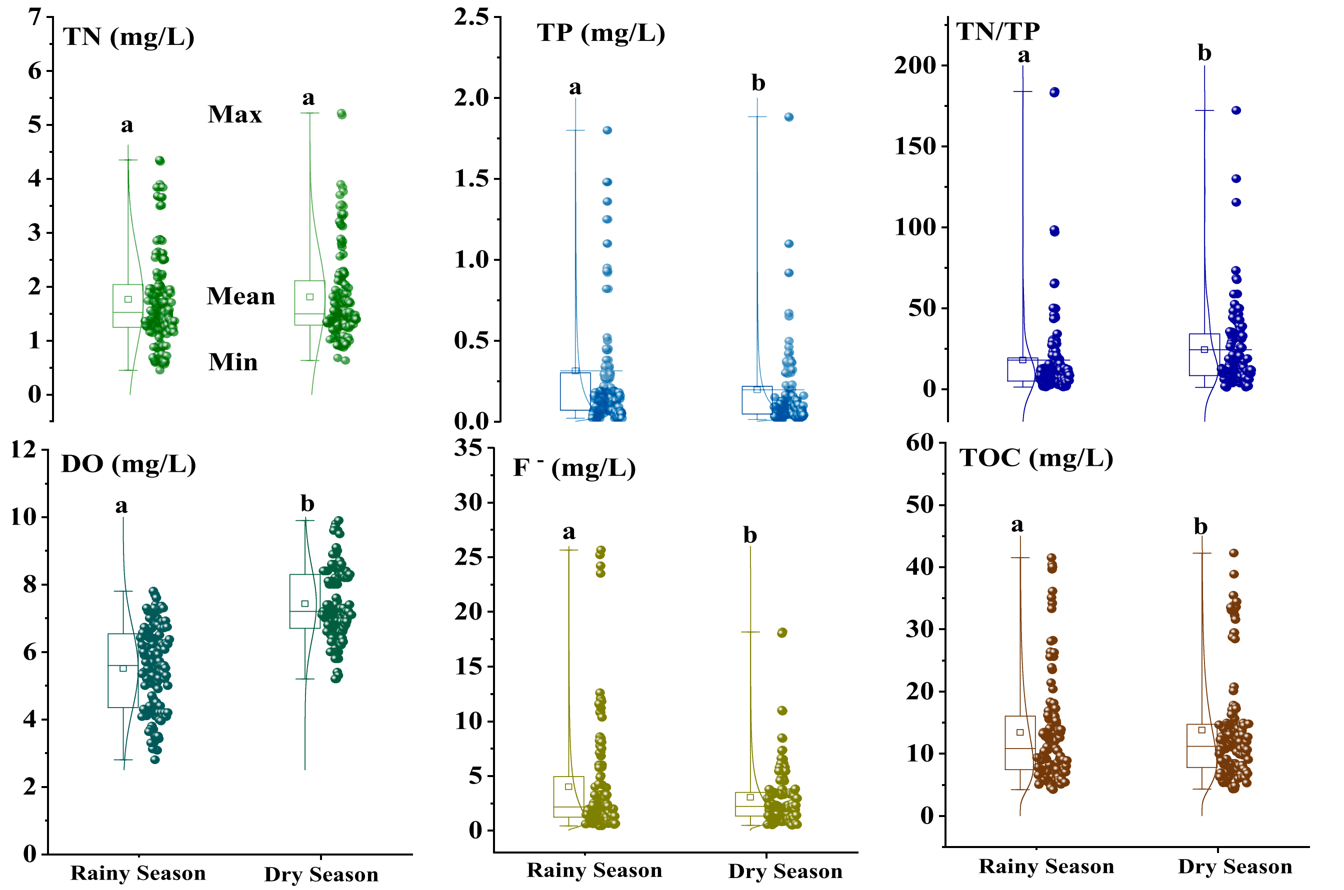


**Fig. 3.** Seasonal changes of TN, TP, TN:TP ratio, DO, $F^-$, and TOC in the lake water over the 2015–2019 period. Different letters above the box indicate a significant difference at the $p < 0.05$ level.

negative impact on water bodies, emphasizing the need to include them in identifying relationships between landscape and water quality (Allan, 2004; Ou et al., 2016; Birk et al., 2020).

The results presented in Fig. 4 indicated that the lakeshore zones of the study area exhibited a high degree of landscape fragmentation, which was closely linked to the proportion of wetlands. A significant decrease in the proportion of wetlands and a sharp increase in cropland area were observed, resulting in an 82.71% decrease in the *PD* value from 50 to 300 m. The findings further suggested that wetlands adjacent to water were highly impacted by anthropogenic activities and exist in a fragmented state, which made it challenging for them to act as effective ecological barriers to intercept and reduce diffuse sources of pollutants. To address this issue, future wetland restoration efforts at the water-land interface zone should focus on building concentrated and continuous large wetland patches, as recommended by Lee et al. (2009). The study also reveals that the landscape complexity was not sensitive to the width of the lakeshore zone, with only a 13.5% decrease in the *ED* value observed with an increase of 250 m in width. This implies that merely increasing the lakeshore zone area may not effectively regulate the complexity of the landscape, and further natural vegetation restoration measures should be taken to smooth the shape of the patches. The spatial aggregation trend of landscape patches was not affected by the width, and the variation of the *CONTAG* value within the lakeshore zone of different widths was around 2%. While the *CONTAG* value of the lakeshore zone characterized the covariation of source-sink landscape, its impact on water quality remained unclear.

### *3.3. Effective riparian/buffer zone width*

The present study aimed to investigate the impact of lakeshore landscapes on water quality using multiple regression coefficients of determination ($R^2$). The results, as depicted in Fig. 5, indicate that during the rainy season, the landscapes within the lakeshore zones of all widths, except for DO and F- variation, were able to effectively predict the water quality parameters. The study found that the highest proportion of TN/TP variation was explained by the landscapes within the first 150 m (i.e., 63.4%). However, the relationship between the landscapes and F- within the first 250 m width was the weakest, explaining only 40% of the variation. The study further revealed that the lakeshore landscapes had a relatively small influence on DO and F-. Only the 150–250 m lakeshore landscapes had a significant correlation with DO, with $R^2$ less than 0.43. Previous research suggests that landscape influences lake DO concentrations through discharges of oxygen-consuming organic matter and shading (regulation of water temperature) (Prairie et al., 2002; Allan, 2004). As illustrated in Fig. 4, wetland fragmentation and low proportion of cropland in the lakeshore zones less than 100 m reduced the shading function, but were also less likely to discharge large pollutants, which may be the main reason for the difficulty of predicting DO changes. We found that as lakeshore width increased (150–250 m), cropland area also rose rapidly, having a significant effect on DO in lake water (Fig. 6). However, as the distance away from the water body became longer, it also made it possible for more contaminants to be intercepted, so the correlation between landscape and DO weakened when lakeshore width reached 300 m.

The lakeshore landscapes within the first 50 m had little influence on F- concentration, and the proportion of the variation explained for other widths was also less than 45%. This was attributed to the fact that saline soil was the only main source of F- input to lake water, resulting in a relatively weak correlation between lakeshore landscapes and F-. However, we found that a certain amount of input (width >50 m) was

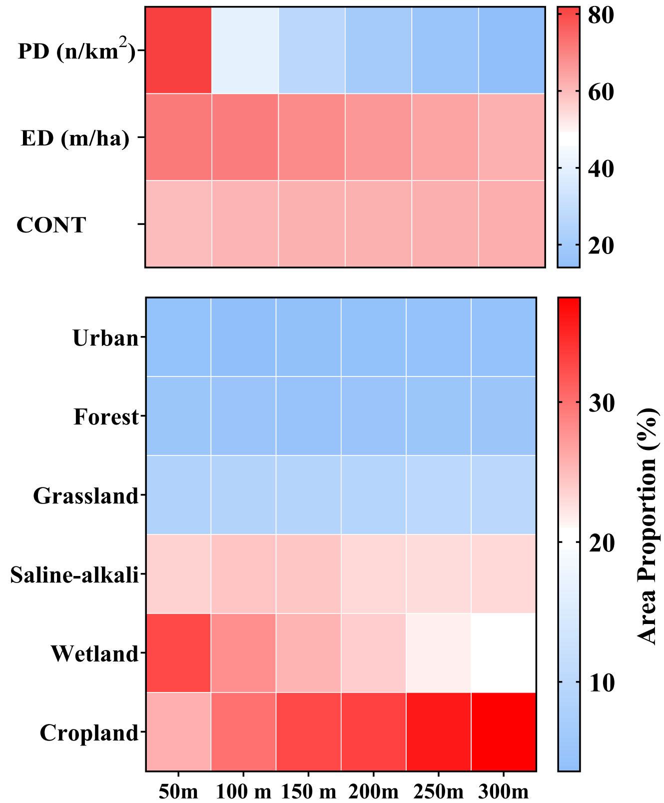


**Fig. 4.** Landscape composition (%) and configuration metrics of the 49 lakes within six lakeshore buffer scales in the Western Jilin Province, China.

needed to have a significant impact. Furthermore, the relationships between landscape prediction ability and water quality for each width of the lakeshore zone were complex and not linearly positive, with a threshold phenomenon observed around 150–200 m (Fig. 5). This finding is consistent with previous research by Guo et al. (2010), who characterized lakeshore buffers of different widths and found that there was a certain width of riparian zone with the strongest linkages between landscape and water quality, but with differences in the effective widths for different water quality parameters. Similarly, Li et al. (2018) examined the relationship between landscape and river water quality in a 100–2000 m wide riparian zone of the Han River basin in central China and found that the landscape within a 300-m wide riparian buffer zone had the largest influence. The study concluded that the correlation between pattern and process had a scale effect and threshold, which is a common phenomenon in landscape ecology (Birk et al., 2020).

As the lakeshore zone width expanded, the influence of the source

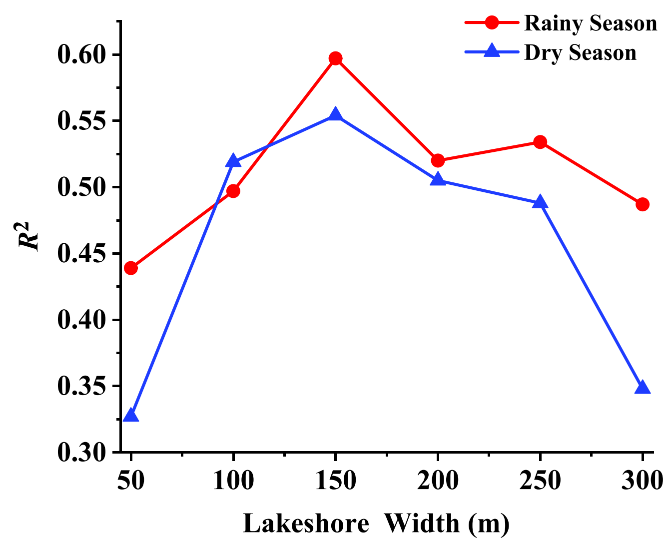


**Fig. 6.** The threshold effect of lakeshore width on predictive power of all landscape variables for overall lake water quality. $R^2$ is the explained proportion of water quality variation from RDA (see Materials and methods).

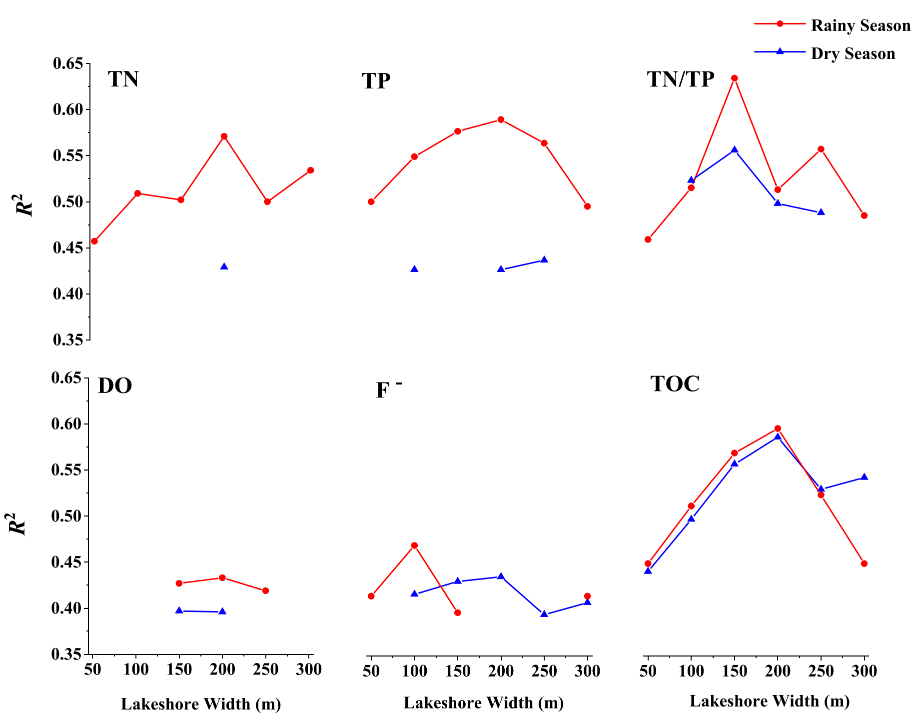


**Fig. 5.** $R^2$ values of multiple linear regressions (MLR) with respect to different lakeshore widths. Only significant models ($p < 0.05$) are shown. $R^2$ is the influence of all landscape variables on a single water quality indicator.

landscape on water quality strengthened and the correlation between the two became more prominent. However, as the distance from the lake increased, pollutants experienced greater interception during transport, leading to a decline in the landscape's impact on water quality after it reached its maximum effect. Additionally, a non-linear relationship between the N:P ratio and landscape type was observed, with a peak in predictive power observed for a 150-m wide lakeshore zone during the rainy season ($R^2 = 0.63$), which was significantly different from other widths of lakeshore zones (Fig. 5). This phenomenon could be attributed to the fact that the source landscape, such as cropland, had multiple influences on the aquatic ecosystem, including simultaneous inputs of both N and P, making the N:P ratio more sensitive and responsive to this stress than a single lake N and P concentration indicator. This suggests that the N:P ratio is a suitable water quality response indicator for identifying the threshold width of the lakeshore zone.

During the dry season, the impact of the lakeshore landscape on water quality decreased rapidly. Among the six parameters studied, only TOC showed a significant correlation with all widths of the lakeshore landscape, while TN only responded to the landscape within the 200-m wide lakeshore. This indicates that runoff played an important role in pollutant transport within the lakeshore zone, particularly for the dissolved form of TN. Consequently, when runoff was low during the dry season, the input of N-pollutants from the source landscape (cropland and urban areas) of the lakeshore zone was effectively cut off, making it difficult to isolate the landscape's effect. However, seasonal changes had little effect on the relationship between TOC and the lakeshore landscape, which was primarily due to the bidirectional regulation of TOC in lake water by wetlands. During the rainy season, when crops were in full growth, wetlands acted as a sink landscape, effectively mitigating oxygen-consuming organic pollutants transported by surface runoff. However, during the dry season, as the organic matter level of surface runoff decreased, wetlands became a source landscape, discharging organic matter into the lake water. As shown in Fig. 5, during the dry season, the landscape was significantly correlated with TN, TP, and DO only when the width of the lakeshore zone exceeded 100 m. This suggests that when surface runoff decreased significantly, the source landscape area had to accumulate to a certain amount to have a significant impact on water quality (Yang et al., 2010).

As shown in Fig. 4, the proportion of cropland increased as the width of the lakeshore zone expanded, which corroborated our findings. Furthermore, compared to the rainy season, the landscape within 100-m lakeshore zone had a greater impact on F- during the dry season. This was primarily due to the strong evapotranspiration during the dry season, which led to increased salt accumulation in the surface layer of the soil. Additionally, the shorter distance to the water body offset the effect of decreasing surface runoff. Ultimately, these two factors combined to enhance the predictive ability of the landscape with regards to changes in F- concentration in the lake water.

Based on the results of the MLR analysis (Fig. 5), the critical range of lakeshore width was determined to be between 150 and 200 m. To refine this critical width range, the RDA was used to investigate the impact of lakeshore landscape on overall water quality. As illustrated in Fig. 6, during the rainy season, the landscape within a 50-m wide lakeshore zone explained the lowest proportion of water quality variability (43.9%), while it was 59.7% within 150 m. During the dry season, the predictive ability of the landscape within both 50-m and 300-m lakeshore zones decreased rapidly to 32.7% and 34.8%, respectively. However, the predictive ability of the landscape within the 150-m wide lakeshore zone on water quality decreased slightly when compared to that during the rainy season, but still had the greatest effect. It was observed that the lakeshore landscape had a greater effect on overall water quality during the rainy season than during the dry season. Nonetheless, the 100-m wide lakeshore zone was more specific, and the landscape had a larger effect during the dry season, mainly due to the more intense $F^-$ exchange between landscape and lake water within this length scale during the dry season. By comparing and integrating the results of MLR and RDA, the critical lakeshore width in the study area was determined to be 150 m (Fig. 6). According to research findings, the variation in critical widths of lake or river riparian zones in different regions is not significant. For example, in the Miyun Reservoir watershed in North China, the critical riparian width was found to be 100 m (Ou et al., 2016) while it was 300 m in the Han River watershed in Central China (Li et al., 2018). Similarly, in Eastern Ontario, Canada, the most influential landscape in terms of N and P concentration in lakes was found to have a lakeshore width ranging from 150 to 300 m (Sawatzky et al., 2019). These results indicate that the critical width of lakeshore/riparian zones as an ecological threshold can be singled out in different regions. The identification framework established in this study, which incorporated water quality and landscape characteristics indicators, was deemed relatively relevant. The combination of MLR and gradient analysis also ensured the robustness of the framework used to identify critical widths. This technical framework has the potential for further application and can be used to conduct related studies in more regions to validate its reliability and applicability.

### *3.4. Linkage between landscape and water quality*

To establish a more precise understanding of the quantitative relationships between lakeshore landscape features and lake water quality, we focused on the 150-m wide lakeshore zone.

According to Table 2, during the rainy season, all water quality parameters could be predicted by landscape features, but the main drivers varied significantly. DO had the weakest correlation with lakeshore landscape ($R^2 = 0.43$) and was only negatively correlated with *PD* and Urban. High-intensity agricultural activities and urban expansion often lead to increased fragmentation of regional landscapes, followed by the influx of oxygen-consuming pollutants into adjacent water bodies, resulting in a decrease in DO levels, which is consistent with the findings of this study. A higher proportion of impervious surfaces was identified as a key parameter of rapid urban expansion, leading to an increase in surface runoff and pollutant export loads (Ou et al., 2016), and a similar decrease in DO levels. All land cover types had a significant influence on TP, with wetlands and grasslands acting as sink landscapes and being negatively associated with TP, while cropland, urban areas, and saline-alkali land acted as source landscapes and were positively associated with TP. Wetlands and grasslands within the lakeshore zone of the study area were effective in reducing P through their ability to trap it through vegetation and sorption by soils, which is consistent with the findings of many studies (Walton et al., 2020). Agricultural activities, rural living, and bare areas were all considered major sources of diffuse pollution, and the results of this study confirmed this widely accepted viewpoint.

*PD* had a greater impact on TN than TP, despite fewer landscape proportion parameters being significantly associated with it. This finding can be attributed to the fact that N pollutants in the study area were mostly dissolved and effectively transported by surface runoff. As the fragmentation of the landscape increased, the transport distance of runoff was extended, resulting in the discharge of more N pollutants into the water body. Furthermore, wetlands within the lakeshore zone were mostly located in the water-land ecotone, leading to a short residence time for TN in the dissolved form, which hindered denitrification (Houlahan and Findlay, 2004). In contrast, grasslands within the lakeshore zone were discrete and could increase the infiltration of TN and utilize part of the N by intercepting surface runoff and increasing transport time, leading to a significant negative correlation with TN (Ou et al., 2016). The study area was characterized by the co-occurrence of heavy precipitation and high temperatures, which served as key climatic features. Consequently, it is highly probable that the lakeshore zone experienced a larger inundated area (low DO) and a rapid proliferation of wetland vegetation during the rainy season.

Numerous studies have demonstrated that environmental conditions conducive to efficient denitrification resulted in less impact on TN level in lakes from source landscapes, such as cropland and urban areas

**Table 2**
Multiple linear regression (MLR) models for each season and water quality parameter for the 150-m buffer zone (n = 49).

| | *PD* | *ED* | *CONTAG* | Wetland | Grassland | Cropland | Urban | Saline-alkali | $R^2$ | *p* |
|---|---|---|---|---|---|---|---|---|---|---|
| *Rainy Season* | | | | | | | | | | |
| DO | – | | | | | | – | | 0.43 | 0.024 |
| TP | | | | – | – | + | + | + | 0.56 | 0.001 |
| TN | + | | | | – | | | + | 0.50 | 0.005 |
| TOC | + | | | – | – | + | | + | 0.54 | 0.002 |
| $F^-$ | | | | | | | | + | 0.43 | 0.022 |
| TN/TP | | | + | | | + | | | 0.63 | 0.001 |
| *Dry Season* | | | | | | | | | | |
| DO | – | | | | | – | | | 0.40 | 0.041 |
| TOC | + | | | – | – | + | + | + | 0.56 | 0.001 |
| $F^-$ | | | | | | | | + | 0.40 | 0.041 |
| TN/TP | | | | | | + | | | 0.56 | 0.001 |

(+) represents a positive correlation, (−) a negative correlation, no symbol represents no correlation; *PD*, patch density; *ED*, edge density; and *CONTAG*, Contagion.

(Hansen et al., 2018; Walton et al., 2020). In contrast, bare saline-alkali land was highly prone to erosion and served as a significant source of N input to lakes, predominantly in sorbed and organic forms, which were more likely to accumulate. As a result, the impact of saline-alkali land on TN was significantly greater than that of cropland and urban areas (Zhang et al., 2007). Similarly, TOC concentrations were also influenced by various landscape features. However, during the rainy season, the rain-scouring effect of impervious ground led to a decrease in TOC levels in surface runoff, indicating that urban areas had little effect on their concentration in lake water. $F^-$ was only correlated with salinity soil, resulting in a low determination coefficient of the linear regression ($R^2$ = 0.43). This suggested that the high background levels of elemental $F^-$combined with the erosion-prone bare saline-alkali soils were primarily responsible for severe $F^-$contamination in lake waters of the study area (Yang et al., 2010).

The TN/TP was found to be most significantly influenced by the lakeshore landscape ($R^2$ = 0.63), with positive correlations observed with both *CONTAG* and cropland. This could be attributed to the fact that agricultural land was a major contributor to diffuse pollution, exporting variety of pollutants such as N and P into the surrounding environment (Wagner et al., 2011). As a result, cropland has a greater impact on lake water quality compared to other types of landscapes. Additionally, higher *CONTAG* values indicated greater connectivity between landscape patches, facilitating the formation and transport of surface runoff and ultimately leading to higher concentrations of N and P in the lake. However, their retention in the landscape of the study area was inconsistent, with greater effectiveness observed in the reduction of P. This explains why *CONTAG* and the ratio of TN/TP were positively correlated.

During the dry season, which is characterized by reduced runoff and lower agricultural activity, the influence of the lakeshore landscape on lake water quality weakens, explaining only the changes observed in DO, TOC, $F^-$, and TN/TP. As a result, the main landscape factors impacting lake water quality underwent slight changes. Furthermore, the ability of landscape pattern metrics to interpret variations in lake water quality also decreased, with only patch density (PD) demonstrating a significant correlation with DO and TOC. Additionally, during the dry season, the accumulation of dry deposits in rural areas, combined with lower temperatures, created favorable conditions for indoor activities among rural residents. This, in turn, lead to the large-scale, unregulated discharge of domestic waste due to the lack of proper treatment facilities (Ting et al., 2021), thereby resulting in increased TOC input from rural areas into the lake waters.

The results obtained from MLR (Table 2) indicated that cropland and saline-alkali land were the dominant landscape factors, with the lakeshore landscape exerting a significant influence on water quality during the rainy season. Furthermore, RDA results (Table 3) showed that the lakeshore landscape explained approximately 60% of the variability in lake water quality during the rainy season, which was 9% higher than that observed during the dry season. Cropland was identified as the most important landscape factor, explaining approximately 30% of the variability in lake water quality, with little effect of seasonal changes on its predictive ability. Conversely, the ability of saline-alkali land to explain changes in lake water quality was significantly affected by the season, with a 42.86% higher explanatory power observed during the rainy season compared to the dry season. Additionally, MLR results (Table 2) revealed that both cropland and saline-alkali land were significantly associated with most water quality indicators, and both played a negative role. Therefore, in combination with the RDA results (Table 3), it could be inferred that intense agricultural activities and soil salinization within the lakeshore zone are the main factors contributing to the deterioration of water quality in the studied lakes.

**Table 3**
The results of redundancy analysis (RDA) demonstrated the percentage variation in overall water quality that could be explained by landscape factors within a 150-meter lakeshore.

| | Explained variability (%) | | | *p* Value | Key landscape variables (contribution%) |
|---|---|---|---|---|---|
| | Axes1 | Axes2 | All axes | | |
| Rainy Season | 53.4 | 6.0 | 59.7 | 0.01 | Cropland (30.0) Saline-alkali (20.6) |
| Dry Season | 51.4 | 3.8 | 55.4 | 0.01 | Cropland (31.1) Saline-alkali (14.3) |

The *p* values were derived from Monte Carlo permutation tests (499 permutations) of all canonical axes.

## 4. Conclusions

In this study, a total of 203 lakes situated in the eco-fragile region of Western Jilin were surveyed, and 49 lakes were selected as representative study sites to explore the correlation between lakeshore landscapes and lake water quality. The study relied on statistical methods to quantitatively identify the relationships between the two types variables during two seasons. The results indicated that most of the studied lakes exhibited significant spatio-temporal variations in water quality parameters, with nutrient pollution being a major concern. Specifically, the concentration of TP in most lakes was almost ten times higher than the national average. The TN/TP ratios of the lakes were low, indicating that N was the limiting factor for phytoplankton growth. Furthermore, the F- concentrations were abnormally high, and according to the Chinese surface water standards, most of the lakes were heavily polluted.

As the width of the lakeshore zone expanded, human activity intensified, and large areas of wetlands were converted into cropland. The impact of lakeshore landscapes on water quality varied between seasons and different water quality parameters. However, the results of MLR and RDA analysis revealed that the influence of the lakeshore landscape on water quality had a threshold value, peaking at a width of 150 m. At this spatial scale, wetlands and grasslands demonstrated a certain purifying effect on water quality. Conversely, cropland and saline-alkali land had the greatest impact on lake water quality, explaining almost 50% of the water quality variability over two seasons. This indicated that agricultural activities were the primary cause of severe nutrient pollution in the studied lakes, while excess $F^-$ was due to severe soil salinisation caused by drought. Therefore, restoration efforts in this region should focus on converting cropland to wetlands within a critical width, creating an effective vegetation buffer zone that promotes denitrification and phosphate deposition. Additionally, green agriculture should be developed to encourage residents to implement saline land improvement projects that inhibit substantial salt input to the lakes.

Based on an analysis of long-term spatio-temporal variations in water quality of 49 typical lakes within a study area of approximately 50,000 $km^2$, this study points towards a dual control approach targeting N and P as an effective strategy for preventing and managing eutrophication in shallow lakes. The research findings indicated that the proportions of cropland and saline-alkali land were the primary landscape factors affecting water quality. This suggested that, at small spatial scales such as lakeshores and riparian zones, landscape composition indicators were more suitable for predicting changes in water quality compared to configuration indicators. These findings provided a foundation for selecting appropriate landscape indicators in future studies investigating the relationship between landscape characteristics and water quality. The successful identification of the critical lakeshore width highlighted the feasibility of the threshold identification framework developed in this study, which integrated water quality analysis, landscape indicator selection, and multivariate statistical methods. Further research is warranted to apply and validate this identification framework.

## CRediT authorship contribution statement

**Yang Ou:** Conceptualization, Funding acquisition. **Alain N. Rousseau:** Writing - review & editing. **Baixing Yan:** Funding acquisition, Data curation.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

The data that has been used is confidential.

## Acknowledgements

This project was funded by National Natural Science Foundation of China (U21A2037 & 41571480), Strategic Priority Research Program of the Chinese Academy of Sciences (XDA23060402 & XDA28080302), and Major Science and Technology Project of the Ministry of Water Resources (SKR-2022039).

## References

Allan, J.D., 2004. Landscapes and riverscapes: the influence of land use on stream ecosystems. Annu. Rev. Ecol. Evol. S. 35, 257–284.
Auditors, E.C.O., 2014. Integration of EU Water Policy Objectives with the CAP: A Partial Success: (pursuant to Article 287 (4), Second Subparagraph, TFEU). Publications Office of the European Union.
Birk, S., Chapman, D., Carvalho, L., Spears, B.M., Andersen, H.E., Argillier, C., Auer, S., Baattrup-Pedersen, A., Banin, L., Beklioğlu, M., 2020. Impacts of multiple stressors on freshwater biota across spatial scales and ecosystems. Nat. Ecol. Evol. 4, 1060–1068.
Boeder, M., Chang, H., 2008. Multi-scale analysis of oxygen demand trends in an urbanizing Oregon watershed, USA. J. Environ. Manag. 87, 567–581.
Chang, L., Zhao, Z., Jiang, L., Li, Y., 2022. Quantifying the ecosystem services of soda saline-alkali grasslands in Western Jilin Province, NE China. Int. J. Env. Res. Pub. He. 19, 4760.
Chen, M., Zeng, G., Zhang, J., Xu, P., Chen, A., Lu, L., 2015. Global landscape of total organic carbon, nitrogen and phosphorus in Lake Water. Sci. Rep. 5, 15043.
Cheng, X., Song, J., Yan, J., 2023. Influences of landscape pattern on water quality at multiple scales in an agricultural basin of western China. Environ. Pollut. 319, 120986.
Danz, N.P., Niemi, G.J., Regal, R.R., Hollenhorst, T., Johnson, L.B., Hanowski, J.M., Axler, R.P., Ciborowski, J.J., Hrabik, T., Brady, V.J., 2007. Integrated measures of anthropogenic stress in the US Great Lakes basin. Environ. Manag. 39, 631–647.
Devito, K., Creed, I., Rothwell, R., Prepas, E., 2000. Landscape controls on phosphorus loading to boreal lakes: implications for the potential impacts of forest harvesting. Can. J. Fish. Aquat. Sci. 57, 1977–1984.
Diebel, M.W., Maxted, J.T., Robertson, D.M., Han, S., Vander Zanden, M.J., 2009. Landscape planning for agricultural nonpoint source pollution reduction III: assessing phosphorus and sediment reduction potential. Environ. Manag. 43, 69–83.
Emi Fergus, C., Soranno, P.A., Cheruvelil, K.S., Bremigan, M.T., 2011. Multiscale landscape and wetland drivers of lake total phosphorus and water color. Limnol. Oceanogr. 56, 2127–2146.
Foulon, É., Rousseau, A., Benoy, G., North, R., 2020. A global scan of how the issue of nutrient loading and harmful algal blooms is being addressed by governments, non-governmental organizations, and volunteers. Water Quality Res. J. 55, 1–23.
Groffman, P.M., Baron, J.S., Blett, T., Gold, A.J., Goodman, I., Gunderson, L.H., Levinson, B.M., Palmer, M.A., Paerl, H.W., Peterson, G.D., Poff, N.L., Rejeski, D.W., Reynolds, J.F., Turner, M.G., Weathers, K.C., Wiens, J., 2006. Ecological thresholds: the key to successful environmental management or an important concept with no practical application? Ecosystems 9, 1–13.
Gu, Z., Bian, J., Wu, J., Ruan, D., Yu, Y., Zhang, H., 2022. Effects of anthropogenic activities on hydrochemical characteristics of ground water of Da'an irrigation area in Western of Jilin Province. Environ. Sci. Pollut. R. 29, 20479–20495.
Halse, S.A., Massenbauer, T., 2005. Incorporating research results into wetland management: lessons from recovery catchments in saline landscapes. Hydrobiologia 552, 33–44.
Hansen, A.T., Dolph, C.L., Foufoula-Georgiou, E., Finlay, J.C., 2018. Contribution of wetlands to nitrate removal at the watershed scale. Nat. Geosci. 11, 127–132.
Hanson, P.C., Carpenter, S.R., Armstrong, D.E., Kratz, S., 2006. Lake dissolved inorganic carbon and dissolved oxygen: changing drivers from days to decades. Ecol. Monogr. 76, 343–363.
Houlahan, J.E., Findlay, C.S., 2004. Estimating the'critical'distance at which adjacent land-use degrades wetland water and sediment quality. Landscape Ecol. 19, 677–690.
Huel, D., 2000. Managing Saskatchewan Wetlands, a Landowner's Guide. Saskatchewan Wetland Conservation Corporation.
Jabal, Z.K., Khayyun, T.S., Alwan, I.A., 2022. Impact of climate change on crops productivity using MODIS-NDVI time series. Civ. Eng. J. (Iran) 8, 1136–1156.
Kelly, R.P., Erickson, A.L., Mease, L.A., Battista, W., Kittinger, J.N., Fujita, R., 2015. Embracing thresholds for better environmental management. Philos. T. R. Soc. B. 370, 20130276.
Klose, K., Cooper, S.D., Leydecker, A.D., Kreitler, J., 2012. Relationships among catchment land use and concentrations of nutrients, algae, and dissolved oxygen in a southern California river. Freshw. Sci. 31, 908–927.
Larsen, S., Andersen, T., Hessen, D.O., 2011. Climate change predicted to cause severe increase of organic carbon in lakes. Glob. Chang. Biol. 17, 1186–1192.
Lee, S.W., Hwang, S.J., Lee, S.B., Hwang, H.S., Sung, H.C., 2009. Landscape ecological approach to the relationships of land use patterns in watersheds to water quality characteristics. Landsc. Urban Plann. 92, 0–89.
Lee, P., Smyth, C., Boutin, S., 2004. Quantitative review of riparian buffer width guidelines from Canada and the United States. J. Environ. Manag. 70, 165–180.
Li, K., Chi, G., Wang, L., Xie, Y., Wang, X., Fan, Z., 2018. Identifying the critical riparian buffer zone with the strongest linkage between landscape characteristics and surface water quality. Ecol. Ind. 93, 741–752.
Liu, X., Chen, L., Zhang, G., Zhang, J., Wu, Y., Ju, H., 2021. Spatiotemporal dynamics of succession and growth limitation of phytoplankton for nutrients and light in a large shallow lake. Water Res. 194, 116910.
Machado, F., Anderson, K., 2016. Brazil's new Forest Code: a guide for decision-makers in supply chains and governments. WWF, Brasília, DF, Brazil.
Maerki, M., Müller, B., Dinkel, C., Wehrli, B., 2009. Mineralization pathways in lake sediments with different oxygen and organic carbon supply. Limn. Oceanogr. 54.
Manning, D.W.P., Rosemond, A.D., Benstead, J.P., Bumpers, P.M., Kominoski, J.S., 2020. Transport of N and P in U.S. streams and rivers differs with land use and between dissolved and particulate forms. Ecol. Appl. 30, e02130.
McElfish, J.M., Kihslinger, R.L., Nichols, S.S., 2008. Planner's Guide to Wetland Buffers for Local Governments. Environmental Law Institute.
Mironova, N., Yefremova, O., Biletska, H., Bloshchynskyi, I., Koshelnyk, I., Sych, S., Filippov, M., Sinkevych, S., Kravchuk, V., 2022. Soil quality evaluation in urban ecosystems during the covid-19 pandemic. HighTech Innov. J. 3, 43–51.
Nguyen, T.G., Phan, K.A., Huynh, T.H.N., 2022. Application of integrated-weight water quality index in groundwater quality evaluation. Civ. Eng. J. (Iran) 8, 2661–2674.
Ou, Y., Wang, X., Wang, L., Rousseau, A.N., 2016. Landscape influences on water quality in riparian buffer zone of drinking water source area, Northern China. Environ. Earth Sci. 75, 114.

Ou, Y., Rousseau, A.N., Yan, B., Wang, L., Zhang, Y., 2021. Grass barriers for mitigating diffuse pollution within a source water area-A case study of Northeast China. Agr. Water Manage. 243, 106461.
Peters, D.P., Bestelmeyer, B.T., Turner, M.G., 2007. Cross–scale interactions and changing pattern–process relationships: consequences for system dynamics. Ecosystems 10, 790–796.
Polyakov, V., Fares, A., Ryder, M.H., 2005. Precision riparian buffers for the control of nonpoint source pollutant loading into surface water: A review. Environ. Rev. 13, 129–144.
Prairie, Y.T., Bird, D.F., Cole, J.J., 2002. The summer metabolic balance in the epilimnion of southeastern Quebec lakes. Limn. Oceanogr. 47.
Qin, B., Zhou, J., Elser, J.J., Gardner, W.S., Deng, J., Brookes, J.D., 2020. Water depth underpins the relative roles and fates of nitrogen and phosphorus in Lakes. Environ. Sci. Tech. 54, 3191–3198.
Rasmussen, J.J., Baattrup-Pedersen, A., Wiberg-Larsen, P., McKnight, U.S., Kronvang, B., 2011. Buffer strip width and agricultural pesticide contamination in Danish lowland streams: Implications for stream and riparian management. Ecol. Eng. 37, 1990–1997.
Sawatzky, M.E., Fahrig, L., 2019. Wetland buffers are no substitute for landscape-scale conservation. Ecosphere 10, e02661.
Shi, P., Zhang, Y., Li, Z., Li, P., Xu, G., 2017. Influence of land use and land cover patterns on seasonal water quality at multi-spatial scales. Catena 151, 182–190.
Sitati, A., Raburu, P.O., Yegon, M.J., Masese, F.O., 2021. Land-use influence on the functional organization of Afrotropical macroinvertebrate assemblages. Limnologica 88, 125875.
Song, K., Wen, Z., Shang, Y., Yang, H., Lyu, L., Liu, G., Fang, C., Du, J., Zhao, Y., 2018. Quantification of dissolved organic carbon (DOC) storage in lakes and reservoirs of mainland China. J. Environ. Manag. 217, 391–402.
Stoddard, J.L., Van Sickle, J., Herlihy, A.T., Brahney, J., Paulsen, S., Peck, D.V., Mitchell, R., Pollard, A.I., 2016. Continental-scale increase in lake and stream phosphorus: Are oligotrophic systems disappearing in the United States? Environ. Sci. Tech. 50, 3409–3415.
Taş, B., Tepe, Y., Ustaoğlu, F., Alptekin, S., 2019. Benthic algal diversity and water quality evaluation by biological approach of Turnasuyu Creek, NE Turkey. Desalin. Water Treat. 155, 402–415.
Ting, L., Mengmeng, Z., Xia, P., Qiuxiang, H., Shengzhong, D., 2021. Study on the present situation and strategies of rural waste classification treatment in Northeast China. Asian Agric. Res. 12, 30–32.
Tong, Y., Zhang, W., Wang, X., Couture, R.M., Larssen, T., Zhao, Y., Li, J., Liang, H., Liu, X., Bu, X., 2017. Decline in Chinese lake phosphorus concentration accompanied by shift in sources since 2006. Nat. Geosci. 10, 507–511.
Tong, Y., Wang, M., Peñuelas, J., Liu, X., Lin, Y., 2020. Improvement in municipal wastewater treatment alters lake nitrogen to phosphorus ratios in populated regions. P. Natl. Acad. Sci. USA 117, 11566–11572.
Tong, Y., Huang, Z., Janssen, A.B.G., Wishart, M., He, W., Wang, X., Zhao, Y., 2022. Influence of social and environmental drivers on nutrient concentrations and ratios in lakes: A comparison between China and Europe. Water Res. 227, 119347.
Tsegaye, T., Sheppard, D., Islam, K.R., Tadesse, W., Atalay, A., Marzen, L., 2006. Development of chemical index as a measure of in-stream water quality in response to land-use and land cover changes. Water Air Soil Poll. 174, 161–179.
Ury, E., Arrumugam, P., Herbert, E.R., Badiou, P., Page, B., Basu, N.B., 2023. Source or sink? Meta-analysis reveals diverging controls of phosphorus retention and release in restored and constructed wetlands. Environ. Res. Lett. 18, 083002.
Ustaoğlu, F., Tepe, Y., 2019. Water quality and sediment contamination assessment of Pazarsuyu Stream, Turkey using multivariate statistical methods and pollution indicators. In. Soil Water Conse. 7, 47–56.
Wagner, T., Soranno, P.A., Webster, K.E., Cheruvelil, K.S., 2011. Landscape drivers of regional variation in the relationship between total phosphorus and chlorophyll in lakes. Freshwater Biol. 56, 1811–1824.
Walton, C.R., Zak, D., Audet, J., Petersen, R.J., Hoffmann, C.C., 2020. Wetland buffer zones for nitrogen and phosphorus retention: Impacts of soil type, hydrology and vegetation. Sci. Total Environ. 727, 138709.
Wang, Z., Song, K., Zhang, B., Liu, D., Ren, C., Luo, L., Yang, T., Huang, N., Hu, L., Yang, H., 2009. Shrinkage and fragmentation of grasslands in the West Songnen Plain, China. Agr. Ecosyst. Environ. 129, 315–324.
Wu, J., Lu, J., 2019. Landscape patterns regulate non-point source nutrient pollution in an agricultural watershed. Sci. Total Enviro. 669, 377–388.
Xu, Q., Yan, T., Wang, C., Hua, L., Zhai, L., 2023. Managing landscape patterns at the riparian zone and sub-basin scale is equally important for water quality protection. Water Res. 229, 119280.
Yang, J., Zhang, S., Li, Y., Bu, K., Zhang, Y., Chang, L., Zhang, Y., 2010. Dynamics of saline-alkali land and its ecological regionalization in western Songnen Plain, China. Chinese Geogr. Sci. 20, 159–166.
Zhang, X., Chen, L., Yu, Y., Shen, Z., 2021. Water quality variability affected by landscape patterns and the associated temporal observation scales in the rapidly urbanizing watershed. J. Environ. Manag. 298, 113523.
Zhang, B., Hong, M., Zhang, B., Zhang, X.L., Zhao, Y.S., 2007. Fluorine distribution in aquatic environment and its health effect in the Western Region of the Songnen Plain, Northeast China. Environ. Monit. Assess. 133, 379–386.
Zhang, J., Li, S., Dong, R., Jiang, C., Ni, M., 2019. Influences of land use metrics at multi-spatial scales on seasonal water quality: A case study of river systems in the Three Gorges Reservoir Area, China. J. Clean Prod. 206, 76–85.