Estimating the pollutant loss rate based on the concentration process and landscape unit interactions: a case study of the Dianchi Lake Basin, Yunnan Province, China

Minghao Wang¹,² · Yong Wang¹ · Lijie Duan² · Xiaoyang Liu³ · Haifeng Jia² · Binghui Zheng¹,²

Received: 7 December 2021 / Accepted: 9 March 2022 / Published online: 10 June 2022 © The Author(s), under exclusive licence to Springer-Verlag GmbH Germany, part of Springer Nature 2022

Abstract
The landscape analysis model establishes a quantitative relationship between landscape patterns and pollution processes. The spatial heterogeneity within and between landscapes affects the pollutant transmission process and originates from the superposition effect of terrestrial geographical and morphological characteristics. This study aimed to develop a new method to estimate the pollutant loss rate. From the perspective of the flow process of pollutants entering a water body, the interaction between each landscape unit and adjacent unit during pollutant migration was simulated along the pollutant migration flow path. The role of pollutants affected by external forces in the process of migration could be divided into “promoting” and “hindering.” Four indices were proposed to simulate the pollutant loads entering the lake. The linear coefficients between the load of the pollutants chemical oxygen demand (COD$_{Cr}$), ammoniacal nitrogen (NH3-N), total nitrogen (TN), and total phosphorus (TP) entering the lake and the pollutant load emission weighted by the upstream and downstream confluence ratio index were 0.930, 0.835, 0.925, and 0.795, respectively, and the non-linear variance explanation coefficients were 87.70%, 87.50%, 87.60%, and 84.70%, respectively. When the surface resistance was integrated into the index as a parameter, the linear and nonlinear correlation coefficients were significantly improved. The linear coefficients were 0.952, 0.897, 0.919, and 0.939, respectively, and the non-linear variance explanations were 99.00%, 97.30%, 95.10%, and 97.30%, respectively. The spatial distribution of landscape surface resistance reflects the spatial movement trend of pollutants from different sources. The indices characterizing the promoting and hindering effects could be integrated to calculate the loss rate of pollutant load entering the lake from landscape units at different locations in the basin space.

Keywords Pollutant loss rate · Concentration process · Landscape pattern · Source sink relationship

Introduction
Lake ecosystems play an important role in maintaining regional ecosystem balance, regulating regional climate, supplementing groundwater sources, regulating and storing excess floodwater, and protecting biodiversity and rare species resources (Wang et al. 2021). Moreover, lake ecosystems play a significant role in regional ecological security. The most active social and economic development activities associated with lake systems are typically distributed in the lakeside zone, which is characterized by robust urban–rural construction and represents the development area in lake basins (Wang et al. 2020). Urbanization, industrial development, rapid population growth, and agricultural production activities often lead to an increase in point source and non-point source (NPS) pollutants (Li et al. 2010; Liu et al. 2021b). The issues of territorial ecological space occupation, watershed ecosystem degradation, water quality deterioration, and water surface reduction are becoming increasingly severe, resulting in a significant reduction in the ecological self-regulation and restoration function of watershed ecosystems (Li et al. 2021b). After years of ongoing ecological...
rectification and administration, the water environment quality of lakes in China continues to improve; however, these improvement trends show significant fluctuation (Wang et al. 2012). As a result, considerable attention has been paid to the control of industrial pollution. However, the improvement of aquatic environment quality by point source emissions reduction has encountered a bottleneck. Therefore, it is imperative to explore and establish new methods for systematic and long-term lake management (Efstratiadis and Hadjibiros 2011).

The correlation between land use and lake water quality changes has a complex spatial and temporal relationship and is also influenced by additional factors (Nielsen et al. 2012). The development and application of landscape ecology provide new perspectives and ideas for environmental science research (Post 1996; Turner and Gardner 2015). The landscape is a heterogeneous or patchy spatial unit consortium based on land use and is composed of various ecosystem types, representing a composite mosaic that can reflect the comprehensive characteristics of meteorology, climate, ecological processes, and the social economy (Turner 2005; Wu 2013). The reclassification of landscape types from the perspective of source and sink is widely recognized by researchers and allows for the clarification of all the functions and properties of land use in the process of pollution mitigation. Moreover, the impact of land use scale and spatial patterns on lake water quality can be determined based on scale pattern relationships and used to identify landscape ecosystems susceptible to pollutants in the basin and to control nutrient loss and transmission processes (Chang et al. 2021; Li et al. 2017; Ouyang et al. 2010b).

The NPS pollution exhibited characteristics of multiple governing factors, complex and changeable processes, spatial heterogeneity, and temporal fluctuation (Zou et al. 2020). At present, the basic premise of simulating NPS pollution migration and transmission processes is a constant influence of environmental variables on the process of NPS pollution. However, in the landscape mosaic, which is affected by topography, climate, vegetation conditions, and human activities, the energy flow and logistics state between heterogeneous patches are complex and changeable (Varekar et al. 2021). Moreover, landscape patterns on lake water quality by changing processes such as material exchange, hydrological processes, and soil erosion between landscapes (Guo et al. 2021; Liu et al. 2011) are the primary processes involved in the formation and development of watershed pollution (Li et al. 2008). Landscape metrics describe the landscape spatial structure and are the primary methods used to study the impact of landscape patterns on water quality (Xu et al. 2020; Yuan et al. 2015). Ouyang et al. used patch density, edge density, fractal distribution index, and other indicators to express the landscape pattern and determined that various landscape types produced different effects on the nitrogen and phosphorus loads of water systems (Ouyang et al. 2010a). Moreover, Xia et al. reported that water quality is susceptible to changes in landscape patterns, with construction and cultivated land showing a positive correlation with the water pollution index and higher forest coverage correlating to better water quality (Xia et al. 2012).

Although landscape metrics are widely used in the analysis of landscape patterns, most researchers consider the type, quantity, and spatial allocation of landscape features as independent variables when analyzing the effects of landscapes on watershed pollution without considering the influence of process mechanisms or the coupling relationship between landscape scale and spatial allocation (Li et al. 2021a). The watershed pollution process is a multiscale and nonlinear spatially explicit process. The conventional landscape metric lacks consideration of scale pattern relationships and process pattern relationships; thus, it is challenging to accurately describe the migration and diffusion processes of watershed pollutants (Winslow 2014).

The spatially explicit landscape model typically divides the landscape into different geospatial units according to the landscape function and establishes the relationship between the landscape and the watershed pollution process by describing the characteristics of the units and the ecological flow process between the units (Nobre et al. 2020; Nowosad and Stepinski 2019). Because this model fully incorporates the characteristics of ecosystems, topography, and other aspects, it can be used to accurately describe the energy and material exchange processes between spatial units and simulate the watershed pollution process. Existing research on material migration and energy flow has provided theoretical support and laid a good foundation for establishing ecological process-based models (Sampson et al. 2006). According to the functions of different landscape types in landscape ecology, landscapes can be divided into “source” and “sink.” The source landscapes are landscape units (patches) that positively promote the pollution process, whereas the sink landscapes refer to the landscape units (patches) that negatively inhibit or delay the occurrence of the pollution process or the diffusion of pollutants. According to the source-sink theory, the fundamental cause of watershed pollution and pollutant diffusion is the unbalanced profit and loss of nutrients in the landscape unit. When the amount of pollutants generated or received in the landscape unit or patch exceeds its functional threshold, pollutant diffusion and loss will occur. Source-sink landscape models are based on the source-sink landscape function and integrate the coupling relationship between landscape spatial characteristics and ecological processes to establish the internal relationship between landscape variables and watershed pollution processes.

This study aimed to reveal the response law of watershed pollutant load to land use composition and pattern and
determine the influencing factors and response law of lake water quality change. Based on our findings, a lake water quality simulation model was proposed to solve the problem of insufficient expression of spatial processes in the existing models. We combined the principles of landscape ecology with the process of non-point source pollution. The method constructed in this paper focuses on the ability of landscape patterns in nutrient collection and highlights the role of landscape patterns. The nutrient interception equation considered the pollution production and nutrient interception capacity of the landscape and highlighted the role of landscape units. To achieve these aims, the following procedures were followed: (1) obtaining the land use/cover vector data in the study area using remote sensing data interpretation and analyzing the temporal and spatial differences of land use/cover; (2) calculating the amount of pollutants entering the lake, and analyzing the composition and spatial structure of the pollution source; (3) identifying the response relationship between pollutant emissions and pollutant inflow into the lake; and (4) proposing an estimation method for pollutant load loss rate.

Materials and methods

Study area

The lake analyzed in this study was the Dianchi Lake, which is the largest freshwater lake in Yunnan Province, China, and is located in the southwest of Kunming (Fig. 1). Moreover, this lake is the primary source of the Pudu River, a tributary of the Jinsha River, the mainstream of the upper reaches of the Yangtze River. Affected by topography and geological structure, the Dianchi Lake is a typical semi-closed, shallow lake. The Dianchi Lake Basin (102°29–103°01 E, 24°29–25°28 N) is located in the Jinsha River water system basin, with a drainage area of 2920 km². The altitude ranges from 1887 to 2811 m.

Diagenetic parent rocks in the Dianchi Lake Basin include sandstone, shale, purple sandstone, limestone, argillaceous sandstone, and basalt. Because of the different diagenetic parent rocks and soil-forming processes that occur in and around the lake, the soil formed is different from the rest of the region. The Dianchi Lake belongs to the Yangtze River basin. The surface and drainage areas of Dianchi Lake are approximately 309 km² and 2920 km², respectively. The annual average precipitation in the Dianchi Lake area, most of which occurs in the form of rainfall, is 917.93 mm, and evaporation from the lake is 1426 mm per annum. The average air temperature was 14.7 °C, and the evaporation from the lake, which amounts to 1409 mm per year, typically exceeds the rainfall. In 2020, the total resident population of the Dianchi Lake Basin was 4.136 million, including an urban and rural population of 3.832 million and 304 000, respectively. The GDP of basin settlements is 518.07 billion Yuan.

The river network is an essential fundamental geographic information element and primary hydrological parameter. The whole basin is divided into 25 primary sub-basins and 2932 secondary sub-basins (Fig. 2), using a river network and a digital elevation model (DEM) (downloaded from https://srtm.csi.cgiar.org/srtmdata).

Data source

Land use and land cover

The remote sensing images used in this study were Landsat data, which can be downloaded from the Earth Resources Observation and Science (EROS) Center (https://earthexplorer.usgs.gov), and incorporates Landsat-5, Landsat-7, and Landsat-8 data, with an image resolution of 30 m. The Landsat level 2 products released were radiation corrected and geocorrected as well as spatially adjusted to the specified map projection coordinates, which can be used directly as the data source for vector feature extraction. However, image data were preprocessed to improve accuracy, including radiation correction, geometric correction, and fine geometric correction. A DEM was used to correct the parallax caused
by terrain fluctuations. The above processes were completed using RPC orthogonalization in the ENVI5.3 toolbox. We used the object-oriented remote sensing image processing algorithm to divide the land use/cover types into five categories, namely, cultivated land, forestland, grassland, water, and construction land, as well as 11 subcategories, namely, paddy fields, irrigated fields, drylands, forests, shrubby woodlands, mixed forests, grasslands, artificial grasslands, cities, and villages.

Pollutant load emission

Pollutant load refers to the amount of pollutants discharged into the environment by the facilities. Pollutant load generation and the amount entering the lake are the most direct external manifestations of the interaction between pollution sources and receiving water bodies. In this study, the pollutant load was calculated using the pollutant load accounting method of the Second National Census of Pollution Sources. The official data and statistics were used in the calculation, mainly including the municipal and competent state departments such as the Ecological Environment Bureau, the Agriculture and Rural Bureau, the Housing and Urban–Rural Development Bureau, and the Tourism Bureau. Missing data were obtained from on-site supplementary investigations.

Pollution sources in the basin can be divided into two categories and eight subcategories: point source pollution (industry, urban domestic discharge, and tertiary industry) and non-point source pollution (urban runoff, agricultural runoff, livestock and poultry breeding, rural domestic discharge, and soil erosion).

1. Pollutant load generation

The pollution load generations of chemical oxygen demand (COD$_{Cr}$), ammoniacal nitrogen (NH$_3$-N), total nitrogen (TN), and total phosphorus (TP) in the Dianchi Lake Basin in 2020 were 214,760.87, 18,043.76, 37,439.15, and 3460.93 t, respectively (data are listed in Table 1). The process for calculating the pollutant load generation is detailed in the Appendix.

2. Pollutant emission reduction

In 2020, twelve sewage treatment plants were constructed in the Dianchi Lake Basin, which were the Kunming, Chenggong County, and Jinning County sewage treatment plants as well as ten wastewater treatment plants around the lake located in the Yu’ni, Baiyu, Gucheng, Laoyu, Luolong, and Luolong rivers as well as Haikou, Baiyu, and Kunyang. According to the operation data of sewage treatment plants and facilities, COD$_{Cr}$, NH$_3$-N, TN, and TP were reduced to 168,449.79 t, 12,058.90 t, 21,348.49 t, and 2734.83 t, respectively, by sewage treatment facilities in the Dianchi Lake Basin in 2020. Among them, the reduction of point source pollutants was 135,810.32 t, 10,277.72 t, 13,844.02 t, and 1669.87 t, respectively; the reduction in agricultural and rural non-point source pollutants was 17,381.00 t, 1702.19 t, 4909.16 t, and 982.02 t, respectively; and the reduction of urban NPS pollutants was 15,258.48 t, 78.99 t, 2595.31 t, and 82.93 t, respectively.

3. Structural characteristics of pollutant load emission

![Fig. 2 Sub-basins of the study area](image_url)
The discharge of pollutants is defined as the amount of pollutant load generated from the removal of pollutants by urban sewage treatment plants and industrial centralized sewage treatment plants for domestic sewage. In 2020, the discharge of the pollutants COD$_{Cr}$, NH$_3$-N, TN, and TP in the Dianchi Lake Basin was 46,311.08 t, 5984.86 t, 16,090.66 t, and 726.10 t, respectively (see Table 2 for specific data). The emissions of pollutants COD$_{Cr}$, NH$_3$-N, TN, and TP from point sources accounted for 33.58%, 78.76%, 75.60%, and 49.75%, respectively, of the total amount of pollutants.

From the perspective of spatial distribution (Fig. 3), the northern basin accounted for the highest proportion of pollutant load, and the load proportions of COD$_{Cr}$, NH$_3$-N, TN, and TP from this basin were 50.79%, 54.04%, 52.06%, and 49.75%, respectively, of the total amount of pollutants.

Pollutant load into the lake

Pollutant load into a lake or reservoir is a function of the quantities of the polluting materials carried by the inflowing water and the volume of the inflowing water. In this study, pollutant load was calculated using the pollutant concentrations and runoff of the main rivers entering the lake. A total of 34 monitoring sections were set up for rivers entering the Dianchi Lake. The monitoring indicators were COD$_{Cr}$, NH$_3$-N, TN, and TP, and the volume of inflowing river water from January to December 2020 was determined. The river runoff is the primary transport mechanism for pollutants entering the lake in the basin. Based on the tracking investigation of the production and discharge of pollution sources and the loss ways of pollution logistics in the basin, the flux of various pollutants entering the lake was calculated according to the water quantity and quality of the main rivers entering the lake by hydrological stations and monitoring sites.

\[
W = \sum_{i=1}^{12} (C_i \cdot Q_i \cdot T)
\]

(1)

where $W$ was the annual load of pollutants load into the lake (t/a), $C_i$ was the average concentration of pollutants at the
monitoring sites of rivers entering the lake in the \( i \) month (mg/L), and \( Q_i \) was the average flow at the monitoring sites of rivers entering the lake in the \( i \) month (m\(^3\)/s); \( T \) was the duration of \( i \)th month (s).

The pollutant load of the Dianchi Lake River was calculated from water volume and water quality data for the Dianchi Lake River in 2020 (Fig. 4). The results revealed pollutant loads of COD\(_{Cr}\), NH\(_3\)-N, TN, and TP of 22,775.87 t, 1580.70 t, 6700.14 t, and 269.44 t, respectively.

Assessment model

From the perspective of “source-sink” theory, landscape features export NPS pollutants or promote the pollution process in the basin can be regarded as “source” patches, and that can inhibit or slow down the pollution process referred to as “sink” patches (Li et al. 2017). Generally, researchers regard cultivated land, construction land, and unused land in the basin as source landscapes as they promote pollution processes, whereas forestland, grassland, and wetlands, which are characterized by a pollutant interception function, are regarded as sink landscapes (Li et al. 2017). The interaction between source-sink landscapes is through the mechanism of “flow,” that is, material transmission. Therefore, when analyzing the impact of landscape patterns on the watershed pollution process, we need to consider the spatial configuration of the landscape and the impact of flow change on the correlation process.

According to the principle of distance decay, the closer the source is to the receptor, the more significant is its impact; conversely, the farther away something is, the smaller the impact it has, the lower the spatial proximity effect of geographical variables. Tobler first proposed the geographical law of spatial distance (Tobler 1970). Later, Li proposed using the concept of “flow” to detect the geographical spatial distance and proximity between two geographical units (Li 2007). The definition of flow varies in different scenarios. For watershed pollution, the concept of flow can be used to study the spatial pattern of pollutant transmission...
and diffusion, and the source landscape exerts an effect on the receiving water body through numerous flows.

**Migration flow path**

The intensity of the effect of watershed landscape units on receptors can be measured from four aspects: spatial distance, relative elevation, slope (Chen et al. 2008; Wang et al. 2019), and runoff dynamics. It is generally believed that the shorter the distance, the more significant is the contribution. Moreover, the smaller the relative elevation, the shorter the vertical distance, and the greater the impact on the receptor. The greater the slope, the higher the risk of nutrient loss, and the greater the impact on the receptor (Liu et al. 2021a). When the runoff dynamics exceed the sink landscape’s interception function threshold, the role of the sink landscape is diminished and can be transformed into a flow (Chen et al. 2003).

The spatial flow path in the basin can be used to describe the potential hydrological process of pollutant transport on the surface of the basin and the migration and diffusion processes of pollutants associated with the hydrological process (Katis et al. 2018). Moreover, the flow path could be calculated according to the geometric elevation and slope, and the confluence path length was used to characterize the action distance between the source and the receptor (Lanni et al. 2012).

The loss of nutrients produced by the source landscape unit is promoted by several dynamic processes. Therefore, when the balance state of nutrients or pollutants is disturbed by the external force of the unit, the migration and diffusion of pollutants will occur, and the cumulative runoff from upstream will be the source of the primary dynamics. A significant correlation was found between the cumulative runoff and cumulative sediment yield and runoff duration (Xia et al. 2021; Yang et al. 2021).

We calculated the pollutant migration flow path based on the elevation grid map, as shown in Fig. 5a, and the migration direction was determined by the eight-direction (D8) flow model (OCallaghan and Mark 1984), which contains eight adequate directions on each grid (Fig. 5b). In this model, it is assumed that the pollution flow in a grid flows out of the grid in one direction only; thus, the migration direction is determined according to the relative elevation with the surrounding grid.

Graph theory is an essential mathematical field that originated from the Swiss mathematician Leonard Euler’s study of the Seven Bridges of Königsberg (Alexanderson and Gerald, 2006). It is a graph model that describes the attributes of objects and their relationship in an abstract way, based on the classification, properties, and characteristics of graphs. The nodes can represent objects, groups, habitats, and their spatial location or attribute information (Fig. 6). The edges can represent the causal relationship, logical relationship, and spatial relationship between objects (Ziolkowska et al. 2014). Theoretically, the processes in basins present prominent graph properties prominently. The spatial location of objects shows the difference of spatial configuration, and the relationship between them can characterize their confluence process. The application of graph theory can simplify the description of the watershed confluence process.

The flow path can only move from one grid to the next along the maximum elevation gradient until it reaches a sink patch, geographical depression, or watershed boundary (outlet) (Fig. 7). The runoff direction will be randomly configured when there are two or more directions with the same maximum elevation gradient. Typically, a large number of grids occur in a given area, so the random
configuration of this direction can be ignored. The distance from one grid to the next adjacent grid (if any) is the length of the distance along the slope between the centers of the two grids. The calculation of the confluence path was based on the single-flow direction method.

**Interaction between units**

After constructing the pollution flow path, the connection between landscape units was determined through the pollution migration path, as shown in Fig. 8, where the cumulative upstream units of unit \( k \) are represented by the light green filled area, and the cumulative upstream units are the collection of upstream units of all upstream confluence paths passing through unit \( k \). The downstream accumulation units are indicated in yellow, and the downstream accumulation unit is the collection of all downstream units passing through the confluence path of unit \( k \).

**Promoting and hindering effects**

The pollutant migration capacity is related to the migration path length of the material flow, the interception of the underlying surface of the downstream unit, and its own pollution production capacity. The flow velocity has a negative correlation with vegetation coverage and surface roughness. In the process of downstream confluence, the greater the
vegetation coverage or surface roughness of the landscape unit, the more excellent the resistance to migration and the smaller the ability of pollutants to enter the lake. The greater its own pollution production capacity or upstream migration power, the greater the possibility of pollutant migration into the lake.

The pollutant collection process is the migration and diffusion of pollutants under the dynamic conditions brought by the accumulated precipitation upstream. The promoting source is mainly the runoff upstream, and its transmission capacity increases with the increase of runoff. During the migration of pollutants on the downstream transmission path, the hindering effect comes from the underlying surface characteristics (e.g., surface cover, soil characteristics).

Cumulative dynamic and hindrance ratio index

The cumulative dynamic and hindrance ratio index was used to measure the pollutant export capacity of the source landscape units under the joint influence of dynamic action and the distance effect. The pollutant generation process of the landscape units under dynamic conditions resulted from cumulative precipitation from the upstream area. When the nutrients or pollutants were disturbed by the external force of the unit and the equilibrium state was disturbed, pollutant migration and diffusion occurred, and cumulative runoff from upstream represented the primary dynamic source. In the process of pollutant migration along the downstream confluence path, the total pollutant loss was affected by the resistance of landscape units, and the migration capability improved with the increase of runoff. The longer the cumulative confluence path upstream of the patch, the greater the runoff dynamics. Moreover, the shorter the downstream path, the lower the confluence loss. Equations 2–7 describe the relationship between the quantities of pollutant into the lake and the spatial characteristics of the landscape units.

\[
\text{Load} = \sum_{k=1}^{K} \left( \frac{\sum_{i=1}^{N_k} \alpha_{ki}RC_{ki}}{\sum_{j=1}^{M_k} \beta_{kp} FLD_{kp}} \right) \times \text{Load}_k \pm \varepsilon \quad (2)
\]

\[
\alpha_{ki} = 1 - C_{ki} \quad (3)
\]

\[
RC_{ki} = \frac{P_{ki}}{Q_{ki}} \quad (4)
\]

\[
Q_{ki} = \begin{cases} 
\frac{(P_{ki} - 0.2S)^2}{P_{ki} + 0.8S} & P_{ki} > 0.2S \\
0 & P_{ki} \leq 0.2S 
\end{cases} \quad (5)
\]

\[
\beta_{kp} = C_{kp} \quad (6)
\]

\[
FLD_{kp} = \sum_{q=1}^{P_p} \frac{FLU_{kp}}{P_p} \quad (7)
\]

where \(\alpha_{ki}\) is the dynamic action coefficient of unit \(i\) on the upstream path of landscape unit \(k\). \(\beta_{kp}\) is the resistance action coefficient of the unit \(p\) on the downstream path of landscape unit \(k\). \(C_{ki}\) is the vegetation coverage of unit \(i\) on the upstream path of landscape unit \(k\). \(P_{ki}\) is the precipitation of unit \(i\) on the upstream path of landscape unit \(k\) (mm). \(Q_{ki}\) is the runoff depth of unit \(i\) on the upstream path of landscape unit \(k\) (mm). \(C_{kp}\) is the vegetation coverage of the unit \(p\) on the downstream path of landscape unit \(k\).
Analysis and results

Migration routes

In this study, the confluence length of downstream (FLD) was used to explain the distance effect of the source-sink space. We defined the FLD as the projection distance on the horizontal plane from the source patches to their destination along the migration route (Fig. 9a). The distribution characteristics of the source patches on the downstream confluence path can be used to explain the risk intensity of the source landscape units owing to the spatial configuration.

The relative spatial position of the landscape units in the basin determines the cumulative runoff. The more upstream confluence is accepted, the greater is the cumulative runoff. The upstream cumulative confluence length (FLU) was used to characterize the cumulative runoff of the landscape units and was defined as the cumulative projection distance on the horizontal plane of all source patches, using a particular point in the basin as the flow endpoint (Fig. 9b).

Linear correlation analysis

The linear correlation between the pollutant load emission weighted by the upstream and downstream confluence ratio index and the pollutant load discharged into the lake is shown in Fig. 10. The Pearson linear correlation coefficients for COD$_{Cr}$, NH$_3$-N, TN, and TP were 0.734, 0.832, 0.898, and 0.732, respectively, which were significant at a 0.01 level. Compared with the unweighted pollutant load emission, the linear correlation coefficient increased by 0.072, 0.013, 0.009, and 0.032.

Non-linear correlation analysis

When the relationship between variables is unclear, generalized additive models (GAMs) can be used to detect the nonlinear correlation of the overall trend of the two sequences. GAM fits the overall trend rather than analyzing the correlation between point values, which allows us to simulate more complex patterns. GAM was developed to explore the non-linear relationship between pollutant load emission weighted by the cumulative dynamic and hindrance ratio index and the pollutant load discharged into the lake. The results are presented in Table 3. Compared with the unweighted load emissions, the variance explanations of the non-linear relationship increased significantly, and the variance explanations of COD$_{Cr}$, NH$_3$-N, TN, and TP in the lake increased by 49.40%, 20.00%, 15.90%, and 29.70%, respectively.

Integrating the weighting factors of source-sink spatial distance, relative elevation, slope, runoff generation power, and migration hindrance can characterize the risk intensity of pollutant export caused by the spatial location of the source landscape patches. In this study, we observed a robust positive correlation between the pollutant load emission weighted by spatial allocation and the load into the lake. Moreover, the source landscape patches showed different risk characteristics at different locations in the basin, with shorter distances between flow paths and water bodies resulting in more significant upstream runoff and ultimately a higher risk of pollution. The influence of the confluence path on
**Fig. 9** Length of flow concentration path in Dianchi basin, a shows the distribution of upstream confluence length, and b shows the distribution of downstream confluence length.

**Fig. 10** Pollutant load emissions and pollutant load inflow entering the lake weighted by upstream and downstream confluence ratio index.
the pollutant load in the lake is not a simple linear relationship. This is because the discharged pollutants from sources close to the water body have better conditions for entering the lake, and the dynamic conditions of units with high runoff accumulation are advantageous.

The pollutant loss rate equation

The transformation of pollutants from the source to the receiving water body is a continuous dynamic process involving three aspects: hydrology, soil erosion, and pollutant migration. In the terrestrial area of the basin, these processes are controlled by natural factors inside or between landscape patches, including meteorological conditions, soil types, vegetation distribution, and topography. These factors control the characteristics of the underlying surface of the basin and affect the flow state of the substances in the basin. The spatial heterogeneity of natural elements plays a different role in the "source-flow–sink" relationship, affecting the difference in landscape pollution load into the lake.

The spatial heterogeneity within and between landscape units affects the transmission process in the actual transmission process of pollutants. This heterogeneity comes from the superposition of underlying surface characteristics (e.g., terrain, vegetation cover, and soil). The surface formed by the superposition of natural factors can be seen as a resistance base surface. It is used to characterize the resistance to be overcome in the transmission process of pollutants in the basin. Pollutants come from the source landscape and arrive at the receiving water body through different resistance units in surface migration. The smaller the cost or work done to overcome the resistance, the greater the possibility of pollutants entering the water body. On the contrary, the greater the cost and work, the smaller the pollution risk.

The migration process of pollutants on the surface, at the landscape level, can be seen as the process of pollutants generated by the landscape unit in the basin migrating from the source landscape and diffusing to the lake to overcome the ground resistance. Because the resistance elements in the basin are complex and have significant spatial dependence, they will be affected by uneven resistance in space. Therefore, the spatial distribution of landscape resistance surfaces can reflect the spatial movement trend of pollutants from different sources.

Seven factors were selected in this study: rainfall erosivity factor (R), soil erodibility factor (K), vegetation cover factor (VI), slope length and slope factor (LS), surface roughness factor (TRI), relative elevation factor (RELE), and terrain wetting index (TWI). The grid layer of each factor was then normalized and reclassified into five grades using the natural breakpoint method. The resistance values were assigned according to the positive and negative correlations between each factor and the NPS pollution process. The resistance values were 1, 3, 5, 7, and 9 from small to large, and the spatial distribution of the single-factor resistance values is shown in Fig. 11.

Finally, the spatial distribution of multifactor composite resistance in the basin was obtained by the weighted summation of seven resistance factors, as shown in Fig. 12.

The resistance coefficient of the pollutant migration process refers to the obstacles encountered by pollutants during movement within and between landscape units with water flow. The downstream landscape resistance value was used to characterize the resistance of substances in the downstream migration process, and the reciprocal of the upstream landscape resistance value was used to characterize the flow production capacity of the unit. We used landscape resistance as a parameter and reconstructed the cumulative dynamic resistance index (Eqs. 8–14). The pollutant loss rate is the proportion of pollution load entering the lake to the emissions from pollution sources. There is no nonlinear relationship between them, showing the explicit spatial relationship with the upstream runoff dynamics and the downstream interception.

$$\text{Load} = \sum_{k=1}^{K} \left( \frac{N_i}{\sum_{j=1}^{M_i} \beta_{ij} \text{Load}_k} \right) \pm \varepsilon$$

$$a_{ki} = \frac{1}{R_{ki}}$$

$$RC_{ki} = \frac{P_{ki}}{Q_{ki}}$$
where $R_{ki}$ was the resistance value of unit $i$ on the upstream path of landscape unit $k$, and $R_{kp}$ was the resistance value of unit $p$ on the downstream path of landscape unit $k$.

The linear correlation between the pollution load emissions weighted by the cumulative dynamic barrier index and the pollution load into the lake is shown in Fig. 13. Pearson’s correlation coefficients of the four pollutants were 0.952, 0.897, 0.919, and 0.939, respectively, which were significant at the 0.01 level. Compared with the unweighted pollutant load emissions of COD$_{Cr}$, NH$_3$-N, TN, and TP, the correlation coefficients increased by 0.290, 0.078, 0.030, and 0.239, respectively.

The non-linear relationship coefficients between the pollution load emission weighted by the cumulative dynamic barrier index and the pollution load into the lake are listed in Table 4. The analysis results showed that compared with the unweighted load emission, the variance explanation of the non-linear relationship
between the pollution load emission and the pollutant load into the lake increased by 50.70%, 19.80%, 13.40%, and 12.60%, respectively.

**Spatial characteristics of pollutant load loss rate**

Figure 14 shows the distribution of the pollutant load loss rate in the Dianchi Lake Basin. The same landscape type was affected by the landscape spatial configuration, resulting in different pollution load capacities in the lake. From the analysis results, we observed that a higher loss rate occurred on the banks of the river and around the lake, rather than the linear change along with the buffer distance, consistent with the results of Qian (Qian 2010). The pollutant load loss rate in the upper reaches of the Panlong River Basin was low, mainly because of the long migration distance of pollutants into the lake, resulting in a significant loss in the process of downstream confluence. The low loss rate in the southern basin was attributed to a small pollutant migration power owing to the short downstream migration path. The low pollutant load loss rate was due to insufficient power, even if the downstream migration path was short.
Identification of crucial pollution sources

Figure 15 shows the spatial characteristics of the TN and TP loads into the lake from the basin, which were calculated by multiplying the pollutant load generation with the pollutant load loss rate. The units that contributed significantly to the pollution load into the lake were distributed in the Caohai Basin, the area upstream of the river, and surrounding the lake. The main reason for the significant pollutant load contribution from the Caohai Basin was the dense urban construction occurring in this basin. Urban NPS pollution contributes significantly to pollution loads into lakes and can discharge a large number of pollutants. In an effort to reduce the high pollution rates in the Caohai Basin, numerous polluting facilities in the basin have been shut down, the industrial layout and structure have been optimized, and the industrial pollution sources have been monitored, resulting in a decline in the proportion of point source pollution loads. Conversely, the impact of NPS pollution generated by urban surface runoff on the water environment of Dianchi Lake has become increasingly prominent. Construction land in the basin is mainly concentrated in the urban area of Kunming. The density of the drainage pipe network in the main urban area is approximately 10.22 km/km², and the maximum centralized collection rate of urban domestic sewage is 75%. The sewage pipe network system can collect sewage discharged on sunny days; however, the load operation of the sewage treatment plant remains high. Two sets of sewage pipe and rainwater pipe network systems were constructed for the main roads, but there were problems of mixed connection of rainwater and sewage and blocking of outlets along the river in the built-up area. Moreover, the rainwater and sewage diversion rates were low, resulting in a high overload rate of the main road pipe network on rainy days. In addition, the sewage collection facilities built had insufficient sewage carrying capacity. The combined sewage overflow pollution caused by explosive runoff pollutant transportation in the rainy season has become one of the crucial factors affecting the water quality of Dianchi Lake. Although agricultural production produces numerous NPS pollutants in areas far away from the rivers, the generated pollution load does not contribute significantly to the amount of pollutants in the lake due to the loss in the migration process. The pollution load generated in the area around the lake flows into the lake with minimal obstruction and thus contributes more significantly to the total pollution of the lake.

| Pollutant | Index weighted Pollutant load emission | Variation |
|-----------|----------------------------------------|-----------|
| COD<sub>c</sub> | 99.00% | <2.00×10<sup>-16</sup>*** | 49.40% |
| NH<sub>3</sub>-N | 97.30% | <2.00×10<sup>-16</sup>*** | 20.00% |
| TN | 95.10% | <2.00×10<sup>-16</sup>*** | 14.00% |
| TP | 97.30% | <2.00×10<sup>-16</sup>*** | 9.60% |

Table 4 Non-linear driving relationship between pollutants entering the lake and pollutant emission weighted by the cumulative dynamic resistance index
Conclusions

The pollution transmission process in the Dianchi Lake Basin is affected by the landscape scale and spatial allocation. During the actual transmission process of pollutants, spatial differences within and between landscapes affect the transmission process due to the superposition effect of land hydrology (meteorological conditions) as well as geographical and morphological characteristics (terrain, vegetation cover, soil). Moreover, the base level formed by the superposition of these natural factors can be regarded as the resistance to be overcome in the transmission process of NPS pollution. The smaller the cost or amount of work required to overcome resistance, the greater the risk of NPS pollution. At the landscape level, the migration process of pollutants can be seen as the process of pollutants generated by the landscape unit migrating from the source landscape and diffusing to the lake to overcome ground resistance. The resistance elements in the basin are complex, diverse, and spatially dependent. During migration, pollutants are affected by spatially uneven resistance. Therefore, the spatial distribution of the landscape resistance surface can reflect the spatial movement trend of pollutants from different sources. Moreover, the response of pollutant migration to source-sink risk patterns leads to differences in the spatial movement trends.

In this study, we determined that meteorological conditions, soil types, vegetation distribution, and landform types changed the surface roughness and heterogeneity of the basin, affecting the pollution migration process and the ease at which pollutants enter the lake. In particular, the resistance of cultivated land, forestland, and construction land to the surface changed significantly. The increase in construction land flattened the runoff path, enabling the pollutants to easily enter the lake. Farming measures, particularly paddy field farming and management, have increased the difficulty of pollutant migration. Forest vegetation can slow down soil erosion and water and soil loss through interception and leaching of the canopy layer and ground cover interception.

The amount of pollution load entering the lake was determined as the load emission weighted by the pollutant load loss rate and was affected by the spatial configuration of the pollution source and the interaction of the landscape units. The retardation effect of several landscape units with large “blocking” effects on nutrient diversions, such as grassland and forestland, was related to spatial allocation. Moreover, a shorter distance between the flow path and the river improved the purification effect on the receiving water body.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s11356-022-19696-9.

Acknowledgements The authors sincerely appreciate the data support by Yunnan Environmental Monitoring Central Station and the remote sensing data obtained from the Earth Resources Observation and Science (EROS) Center (https://earthexplorer.usgs.gov).

Author contribution Minghao Wang: methodology, formal analysis, data curation, validation, data curation.
Yong Wang: visualization, methodology, formal analysis, resources.
Lijie Duan: formal analysis, writing-original draft.
Xiaoyang Liu: investigation, conceptualization, writing-review and editing.
Hailfeng Jia: writing-review and editing, supervision.
Binghui Zheng: project administration, funding acquisition, supervision.

**Funding** This work was supported by the Major Science and Technology Program for Water Pollution Control and Treatment in China under grant numbers 2017ZX07401004 and 2018ZX07701001.

**Data availability** The water quality monitoring data, remote sensing data, and land use/cover used in this study can be available from the corresponding author upon reasonable request.

**Declarations**

**Ethics approval** The work did not involve Human Participants and/or Animals. To the best of our knowledge and belief, this manuscript has not been considered for publication elsewhere.

**Consent to participate** All the authors approved to participate.

**Consent for publication** The authors have reviewed the manuscript and approved it for publication.

**Competing interests** The authors declare no competing interests.

**References**

Alexanderson Gerald L (2006) About the cover: Euler and the Königsberg Bridges: A Historical View. Bulletin (New Series) of the American Mathematical Society 43:567–573

Chang BX, Wherley B, Aitkenhead-Peterson JA, McInnes KJ (2021) Effects of urban residential landscape composition on surface runoff generation. Sci Total Environ 783:146977

Chen LD, Fu BJ, Xu JY, Gong J (2003) Location-weighted landscape contrast index: a scale independent approach for landscape pattern evaluation based on “source-sink” ecological processes. Acta Ecol Sinica

Chen LD, Fu BJ, Zhao WW (2008) Source-sink landscape theory and its ecological significance. Front Biol China 3:131–136

Elfratiadis A, Hadjibiros K (2011) Can an environment-friendly management policy improve the overall performance of an artificial lake? Analysis of a multipurpose dam in Greece. Environ Sci Policy 14:1151–1162

Guo LJ, Liu RM, Men C, Wang QR, Miao Y, Shoaib M, Wang Y, Jiao L, Zhang Y (2021) Multiscale spatiotemporal characteristics of landscape patterns, hotspots, and influencing factors for soil erosion. Sci Total Environ 779:146474–146474

Katis IN, He PJW, Eason RW, Sones CL. (2018) Improved sensitivity and limit-of-detection of lateral flow devices using spatial constraints of the flow-path. Biosens Bioelectron 113:95–100

Lanni C, Borgia M, Rigon R, Tarolli P (2012) Modelling shallow landslide susceptibility by means of a subsurface flow path connectivity index and estimates of soil depth spatial distribution. Hydrol Earth Syst Sci 16:3959–3971

Li NX, Wang J, Yin W, Jia HY, Xu JF, Hao R, Zhong Zm, Shi Zh (2021a) Linking water environmental factors and the local watershed landscape to the chlorophyll a concentration in reservoir bays. Sci Total Environ 758:143617

Li QL, Wei CF, Wang XJ et al (2008) Mechanism and condition of agricultural non-point source pollution. Pedosphere 39:169–176

Li SN, Zhao XQ, Pu JW, Miao PP, Wang Q, Tan K (2021b) Optimize and control territorial spatial functional areas to improve the ecological stability and total environment in karst areas of Southwest China. Land Use Policy 100:104940

Li WF, Cao QW, Lang KL et al (2017) Linking potential heat source and sink to urban heat island: Heterogeneous effects of landscape pattern on land surface temperature. Sci Total Environ 586:457–465

Li XW (2007) The first law of geography and spatial-temporal proximity. Chin J Nat

Li YR, Long HL, Liu YS (2010) Industrial development and land use/cover change and their effects on local environment: a case study of Changshu in eastern coastal China. Front Environ Sci China 4:438–448

Liu J, Yan TZ, Shen ZY (2021a) Sources, transformations of suspended particulate organic matter and their linkage with landscape patterns in the urbanized Beiyun river Watershed of Beijing, China. Sci Total Environ 791:148309–148309

Liu JF, Xu JJ, Zhang X et al (2021b) Nonlinearity and threshold effects of landscape pattern on water quality in a rapidly urbanized headwater watershed in China. Ecol Indic 124:107389

Liu Y, Lv YH, Fu BJ (2011) Implication and limitation of landscape metrics in delineating relationship between landscape pattern and soil erosion. Acta Ecol Sin 31:267–275

Nielsen A, Trolle D, Sondergaard M, Lauridsen TL, Bjerring R, Olesen JE, Jeppesen E (2012) Watershed land use effects on lake water quality in Denmark. Ecol Appl 22:1187–1200

Nobre RLG, Caliman A, Cabral CR et al (2020) Precipitation, landscape properties and land use interactively affect water quality of tropical freshwaters. Sci Total Environ 716:137044

Nowosad J, Stepinski TF (2019) Information theory as a consistent framework for quantification and classification of landscape patterns. Landscape Ecol 34:2091–2101

O’Callaghan JF, Mark DM (1984) The extraction of drainage networks from digital elevation data. Comput Vision Graph Image Proc 28:323–344

Ouyang W, Skidmore AK, Toxopeus AG et al (2010a) Long-term vegetation landscape pattern with non-point source nutrient pollution in upper stream of Yellow River basin. J Hydrol 389:373–380

Ouyang W, Skidmore AK, Toxopeus AG, Hao F (2010b) Long-term vegetation landscape pattern with non-point source nutrient pollution in upper stream of Yellow River basin. J Hydrol 389:373–380

Post DA (1996) Identification of relationships between catchment-scale hydrologic response and landscape attributes. Australian National University, Canberra

Qian S (2010) Modeling non-point pollution based on interactions between flow path and landscape units

Sampson DA, Waring RH, Maier CA et al (2006) Fertilization effects on forest carbon storage and exchange, and net primary production: a new hybrid process model for stand management. For Ecol Manage 221:91–109

Tobler WR (1970) A computer movie simulating urban growth in the Detroit Region. Econ Geogr 46:234–240

Turner MG, Gardner RH (2015) Introduction to landscape ecology and scale, landscape ecology in theory and practice. Springer, pp. 1–32

Turner SJ (2005) Landscape ecology concepts, methods and applications. Landscape Ecol 20:1031–1033

Varekar V, Yadav V, Karmakar S (2021) Rationalization of water harvesting the width of lake riparian buffer zones for improving water quality based on adjustment of land use structure. Ecol Eng 158:106001

Springer
Wang MH, Liu XY, Yang B, Fei Y, Yu JJ, An R, Duan LJ (2021) Heavy metal contamination in surface sediments from lakes and their surrounding topsoils of China. Environ Sci Pollut Res 28:29118–29130

Wang S, Wang W, Chen J, Zhao L, Zhang B, Jiang X (2019) Geochemical baseline establishment and pollution source determination of heavy metals in lake sediments: a case study in Lihu Lake. China 657:978–986

Wang Z, Zhang ZY, Zhang JQ, Zhang YY, Liu HQ (2012) Large-scale utilization of water hyacinth for nutrient removal in Lake Dianchi in China: the effects on the water quality, macrozoobenthos and zooplankton. Chemosphere 89:1255–1261

Winslow LA (2014) Landscape limnology: lake morphology and process at the continental scale. Dissertat Theses - Gradworks

Wu JG (2013) Landscape sustainability science: ecosystem services and human well-being in changing landscapes. Landscape Ecol 28:999–1023

Xia HJ, Kong WJ, Zhou G, Sun OJ (2021) Impacts of landscape patterns on water-related ecosystem services under natural restoration in Liaohe River Reserve, China. Sci Total Environ 792:148290

Xia LL, Liu RZ, Zao YW (2012) Correlation analysis of landscape pattern and water quality in baiyangdian watershed. Procedia Environ Sci 13:2188–2196

Xu S, Li SL, Zhong J et al (2020) Spatial scale effects of the variable relationships between landscape pattern and water quality: example from an agricultural karst river basin, Southwestern China. Agric Ecosyst Environ 300:106999

Yang X, Yang Y, Wan YY, Wu RJ, Feng DK, Li K (2021) Source identification and comprehensive apportionment of the accumulation of soil heavy metals by integrating pollution landscapes, pathways, and receptors. Sci Total Environ 786:147436–147436

Yuan J, Cohen MJ, Kaplan DA, Acharya S, Larsen LG, Nungesser MK (2015) Linking metrics of landscape pattern to hydrological process in a lotic wetland. Landscape Ecol 30:1893–1912

Ziolkowska, Ostapowicz, Radeloff, VC, Kuemmerle (2014) Effects of different matrix representations and connectivity measures on habitat network assessments. LANDSCAPE ECOL 2014,29(9):1551–1570

Zou LL, Liu YS, Wang YS et al (2020) Assessment and analysis of agricultural non-point source pollution loads in China: 1978–2017. J Environ Manage 263:110400

Publisher’s note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.