Lake Victoria's Water Purification Capacity: A Comprehensive Mapping and Human Impact Assessment

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Abstract:

Water purification capacity (WPC), a crucial regulator of aquatic ecosystem services, plays an important role in mitigating non-point source pollution and ensuring water quality in a basin. In this study, the long-term water purification capacity of the three countries surrounding Lake Victoria (Kenya, Tanzania and Uganda) was investigated using multi-source remote sensing data. and furthermore, the relationship between water purification and phytoplankton blooms, as well as anthropogenic activities, was exlored. By applying InVEST model, nitrogen and phosphorus (N/P) retention and output were derived, which were utilized to quantitatively assess reginal WPC. High resolution, long-term (2000-2021) spatial distribution of water purification capacity index (WPI) were then generated. The results reveal significant spatiotemporal changes of WPI, with a general trend of initial decline followed by subsequent increase being observed. Notably, comparatively lower WPI was exhibited by Uganda than by Tanzania and Kenya. Among the anthropogenic factors, the frequency of phytoplankton blooms was identified as serving as a spatial validation of WPI. While a significant negative correlation between WPI and GDP was demonstrated, its correlation with population was found to be considerably weaker. These findings contribute significantly to transboundary water resources management and sustainable development, and provide information support for the maintenance of regional ecological health.

1. Introduction

Water, a fundamental element for sustaining Earth’s life systems (Bilalova., 2023; Li and Wu., 2024), is crucial to ecosystems. Water ecosystems are not only closely related to human life, production and socio-economic development, but also play a protective role for the structure of natural ecosystems and regional ecological environments (Torres et al., 2021; Pickard et al., 2017). However, rapid socio-economic development has intensified the impact on water ecosystems. Coupled with global climate change, this has led to declining water resources, both in quantity and quality, resulting in a continuous degradation of water ecosystem services (Shemer et al., 2023). Among these services, water purification capacity (WPC), which directly influences aquatic ecosystems, has triggered significant attention from researchers globally (Shi et al., 2021).

Methods for assessing WPC are broadly categorized into statistical and empirical models (Rast et al., 2014). Statistical models, typically based on field-collected samples, often face challenges in data collection due to the complexity of some geographical environments (Pearce and Myers, 1990). Empirical models encompass physical and semi-empirical methods. Physical models generally require strong hydrological expertise and the results often lack spatial distribution information (Su et al., 2012; Björklund et al., 2001). Semi-empirical methods, conversely, use datasets to obtain ecological parameters and combine them with ecohydrological processes to estimate WPC. Currently, semi-empirical modeling is the most widely used method for WPC evaluation. However, it is limited by data availability, and the calculated ecological parameters are often inaccurate, which in turn affects the results of WPC evaluation.

The development of RS and GIS technologies, with their wealth of datasets (satellite image data, aerial photography data, etc.), has addressed the data limitations of traditional methods, providing new avenues for studying WPC (Chen et al., 2025; Habeeb and Weli, 2021). Researchers have proposed numerous simulation models by combining socio-economic and multi-source remote sensing data. Commonly used models include SWAT (Myers et al., 2021), TOPMEDEL (Tian et al., 2018), ARIES (Tyrrell, 1999), and InVEST (Yohannes et al., 2021), each capable of evaluating water ecosystem service functions from different perspectives. The InVEST model, in particular, offers advantages in terms of ease of use and simplicity of its underlying principles.

In addition, anthropogenic activities are a primary driver of changes in WPC (Luo et al., 2020). The discharge of substantial amounts of industrial and domestic sewage, along with agricultural runoff containing plant nutrients, into slow moving water bodies can lead to excessive proliferation of aquatic organisms, especially algae. This alter biomass levels and disrupts the ecological balance, impacting water quality (Jing et al., 2024). Many studies have shown that the WPC around lakes is highly correlated with phytoplankton blooms and anthropogenic activities (Lin et al., 2024).

This study mapped the long-term water purification capacity index (WPI) of three countries around Lake Victoria (Kenya, Tanzania and Uganda) based on multi-source remote sensing data and explored its relationship with phytoplankton blooms and anthropogenic activities. This study is significant for promoting local sustainable development and water environment management.

2. Materials

2.1 Study area

Lake Victoria is the largest lake in Africa and the second largest lake in the world after Lake Superior (Ali et al., 2024; Jovanelly et al., 2015). It is located in the East African Plateau, with a lake area of 68,800 km^2, an east-west length of about 350 km, a north-south length of about 400 km, a maximum depth of about 80 m, and an average depth of 40 m. Most of Lake Victoria is within the countries of Tanzania (51% of the lake area) and Uganda (43%), and a small portion belongs to Kenya (6%), which is one of the most densely populated areas in Africa (Swallow et al., 2008).

The Lake Victoria Basin is home to about 45 million inhabitants, whose livelihoods are highly dependent on natural resources (Garg et al., 2023). The Basin's population accounts for 30% of the total population of the countries along the Basin, with a population density of about 300 people/km^2, making it one of the fastest-growing regions in the world. The main economic activities in the Lake Victoria Basin are agriculture, fishery, tourism, etc. More than 85% of the population in the basin rely on agriculture as their main economic and livelihood activities, and it is one of the poorest regions in the world. Among them, agricultural production is the mainstay of the basin's economy, with agriculture consisting mainly of maize, rice, sugarcane, coffee, tea, and dairy products. Export and fisheries are also among the most important economic activities in the basin. In recent years, the basin has become the region with the fastest economic growth rate, but poverty is widespread in the basin.

Since the 1960s, due to the intensification of anthropogenic activities and the invasion of exotic species, the ecosystem of Lake Victoria has been seriously damaged, mainly reflected in the reduction of water transparency and the intensification of eutrophication (Macintyre et al., 2012). Nutrient pollution by N/P has disrupted the original productivity processes of lakes, making phytoplankton such as phytoplankton the absolutely dominant population. phytoplankton now account for about 70% of the phytoplankton biomass. N/P are among the major pollutants in the Lake Victoria basin.

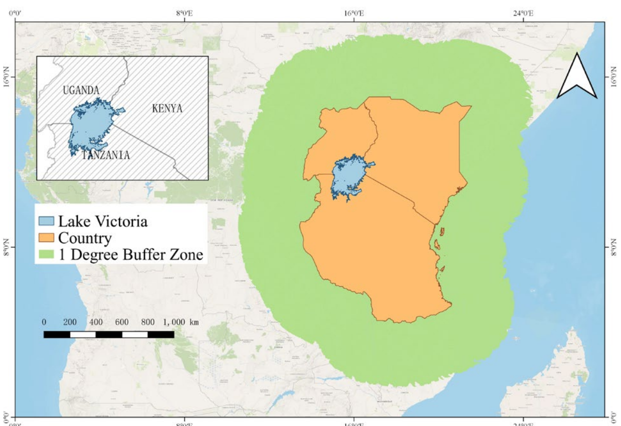

Figure 1. Study area.

The study area and 1 degree buffer zone are shown in Figure 1.

2.2 Data Sources

In this study, the NDR (Nutrient Delivery Ratio) module of the InVEST model was utilized to obtain N/P retention and export data for the study area. The data to be data in the model include digital elevation, land use, precipitation data and biophysical parameters. Among them, the digital elevation data were obtained from General Bathymetric Chart of the Oceans (GEBCO) with a spatial resolution of 15 arc seconds. Land use data were obtained from European Space Agency (ESA), a dataset that provides a global map classifying land surface into 22 categories defined using the Land Cover Classification System (LCCS) of the Food and Agriculture Organization of the United Nations (UN FAO). Precipitation data are from the Global Precipitation Climate Center (GPCC). Biophysical parameters were obtained from the InVEST user's guide and a review of the literature of the region. In addition, phytoplankton bloom data from Lake Victoria, socio-economic data and demographic data were used in the analysis.

Data	Use	Source
DEM	InVEST model	www.gebco.net
Land use	InVEST model	cds.climate. copernicus.eu
Precipitation	InVEST model	opendata.dwd. de
phytoplankton bloom	Verification	Experimental calculation
GDP	Correlation analysis	Worldbank.org
Population	Correlation analysis	landscan.ornl. gov

Table 1. Data sources.

3. Methodology

An integrated framework based on multi-source remote sensing data was proposed to map the long-term WPI of Kenya, Tanzania and Uganda) and explore its relationship with phytoplankton blooms and anthropogenic activities, shown in Figure 2.

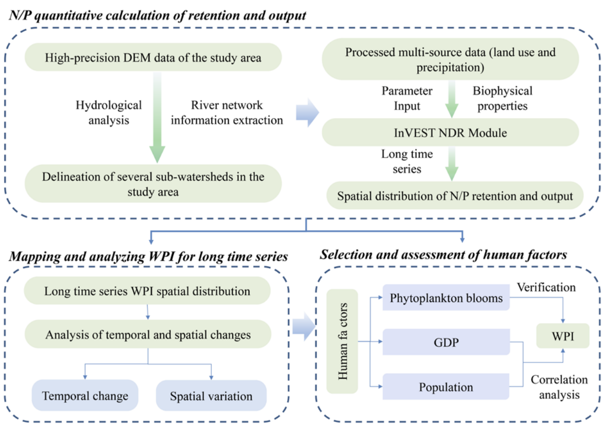

Figure 2. Workflow of this study.

3.1 N/P quantitative calculation of retention and output

The InVEST (Integrated Valuation of Ecosystem Services and Trade-offs) model is an ecosystem service assessment model based on a geographic information system (GIS) combined with actual land use/cover. It has been widely used for ecosystem service assessment at home and abroad.This study utilizes the

Nutrient Transport Rate Module, which is based on the traditional output coefficients and takes into account factors such as topography, runoff, and loss of N/P during transport. The output loads of N/P as they flow into the receiving water body to the outlet can be simulated, so that the purification service capacity of vegetation and soil for N/P nutrients can be mapped later. We pre-processed digital elevation, land use and climate data for the study area and obtained a table of regional biophysical parameters from empirical values and related studies, and input these into the InVEST model to obtain long time-series high-precision N/P retention and export around Lake Victoria.

The InVEST model is run on various types of raster data with the following process: 1) Determine the water flow path based on the input DEM extracting the slope and extracting the river network information. 2) Estimate the pollution output of each parcel by the output coefficients of different land use/cover types. 3) Considering the retention capacity of different land use/cover types, simulate the amount of deposition and retention loss of N/P when migrating between grid cells. 4)Finalize the simulation of spatial distribution of N/P nutrients in the study area.

In the above process, a hydrological sensitivity score was added to the model for the differences between different regions in order to adjust the results to the specific application and make the results more accurate. The specific formulas are as follows:

$$ALV_x = HSS_x \times pol_x \tag{1}$$

where ALV_x is the retention value regulated by grid x, HSS_x is the hydrological sensitivity score of grid x, and pol_x is the corresponding output coefficient.

$$HSS_x = \frac{\lambda_x}{\overline{\lambda_w}} \tag{2}$$

where λ_x is the runoff coefficient of the grid and $\overline{\lambda_x}$ is the average runoff coefficient.

3.2 Mapping and analyzing WPI for long time series

Based on the generated long time series of high-resolution spatially resolved data on N/P retention and export around Lake Victoria, we quantitatively assessed the WPC of the region by calculating a water purification capacity index (WPI). From the N and P calculations, it can be obtained that in some areas, even if the retention of N/P in the watershed maintains an increase in successive years, the N/P export from the watershed will also increase in the same way. It can be seen that it is difficult to accurately assess the water quality purification capacity of a region based only on individual indicators. Therefore, to more directly and accurately quantitatively evaluate the WPC and its spatial and temporal changes in the study area, this study proposes the use of WPI, which evaluates the WPC of a given area by calculating the ratio of the difference between N / P retention and export volume to the sum. The larger the value of WPI, the stronger the WPC of the region.

$$WPI = \frac{reten_{NP} - export_{NP}}{reten_{NP} + export_{NP}} \tag{3}$$

where $export_{NP}$ represents the total N and P output, $reten_{NP}$ represents the total N and P retention.

Using Eq. (3) we mapped high-resolution spatially data of WPI for the long time series of Lake Victoria from 2000 to 2021, which can visualize the spatial and temporal evolution of WPC.

3.3 Selection and assessment of anthropogenic factors

In our study, we chose three anthropogenic effects on WPI, including phytoplankton blooms due to eutrophication of lake water, socio-economic indices and population. Among them, the data of phytoplanktonl blooms are obtained from relevant articles through Landsat images, which can be used as validation data to analyze the surrounding WPI. It can visually reflect the eutrophication of water bodies in the region over a long period of time and the adsorption of nutrients such as N/P by the surrounding vegetation and soil. At the same time, the study obtained the gross domestic product(GDP) of the three countries around Lake Victoria (Kenya, Tanzania and Uganda) from the World Bank and the population distribution data from the Oak Ridge National Laboratory (ORNL) in the United States, as anthropogenic factors to explore its impact on the regional WPC. The study also quantifies the correlation of GDP and population with WPI in the three countries and the study area using the Spearman correlation coefficient.

4. Results

4.1 Analysis of changes in N/P retention and output

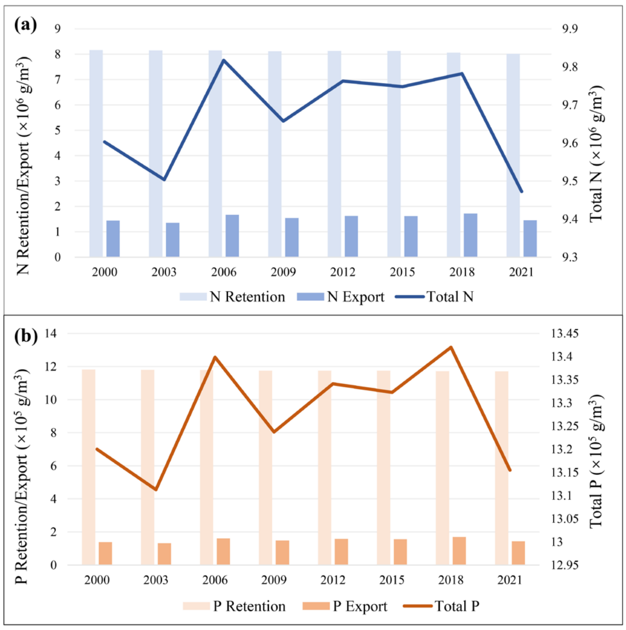

Figure 3. Retention, export and total amount of (a) N and (b) P.

The long-term retention and output of N/P in the study area were calculated (Figure 3) based on the InVEST model. Meanwhile, N/P had basically the same change trend, but the retention and export of N were significantly greater than P. In the long time series, there was no significant change in the retention of N/P, but there was a significant change in the output. The trend in the output of N/P was generally consistent with the trend in total N/P. Total N/P peaked in 2006. Total N peaked at 9.82×10^6 g/m^3 and total P peaked at 1.34×10^6 g/m^3, with total N peaking at 7.3 times that of total P. The total N dropped to the lowest value(9.47×10^6 g/m^3) in 2021, while the lowest value of P(1.31×10^6 g/m^3) appeared in 2003. N/P was at a high level from 2006 to 2018 and decreased after 2018, which was affected by people 's attention to the ecological health of Lake Victoria.

4.2 Spatiotemporal analysis of WPI

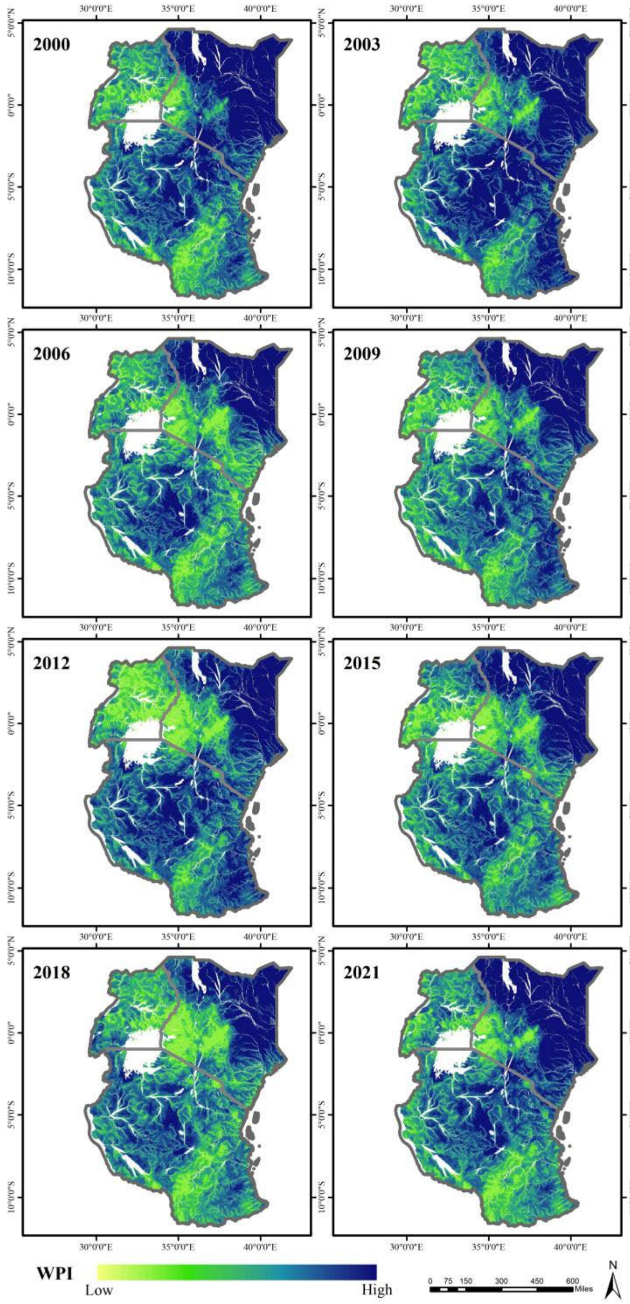

Figure 4. Spatial distribution of WPI around Lake Victoria.

High-resolution maps of WPI around Lake Victoria were generated using data on the spatial distribution of N/P in the long time-series study area (Figure 4). The study also quantified the WPI in the study area and three countries (Figure 5). The results showed obvious spatial differences and changing trends in WPI. In 2000, the northern side of Lake Victoria had a significantly weaker WPI, while the northeastern side had a clear advantage. The southern of Tanzania has a weaker WPI than the rest of the country. Between 2000-2006, the weaker WPI around Lake Victoria shifted along the perimeter of the lake towards the eastern side, and the extent of the weaker WPI increased significantly. Uganda and Tanzania had significantly lower WPI, which was associated with increased regional pollution. The disadvantage of WPI on the northern and eastern sides of Lake Victoria worsened in 2012, while WPI in other areas improved. Between 2012-2018, WPI increased on the northern and western sides of Lake Victoria, but significantly decreased in Tanzania. The year 2021 as a whole was the the highest WPI in the study area, which is related to certain local ecological protection measures.

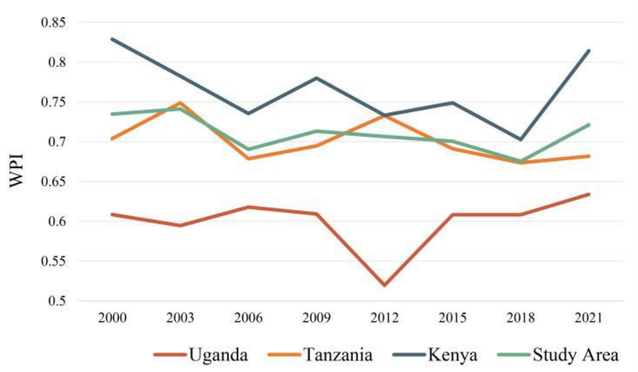

Figure 5. Temporal analysis of WPI.

Meanwhile the statistical results show that the trend of WPI varies from region to region. Of these, Uganda has a significant disadvantage compared to the other regions, which is consistent with the results of the spatial distribution of the wpi data in Figure 4. Uganda's WPI as a whole first declined and then increased, with a minimum value of 0.52 in 2012. WPI change trend in Tanzania showed an "M" shape, with a maximum value of 0.70 in 2003 and a minimum value of 0.67 in 2018. While Kenya's WPI fluctuates with high frequency, taking the highest value of 0.83 in 2000 and the lowest value of 0.70 in 2018. The highest value in Kenya is 1.32 times higher than that of Uganda and the lowest value is 1.35 times higher. The WPI of the study area as a whole fluctuated up and down at 0.7, with the highest value of 0.74 in 2003 and the lowest value of 0.68 in 2018.In summary, WPI has significant spatial and temporal variability, and its spatial and temporal variations are influenced by local anthropogenic activities.

4.3 Assessment of human impacts on WPI

4.3.1 Analysis of the association between phytoplankton blooms and WPI

Figure 6 showed Lake Victoria phytoplankton blooms and WPI of the buffer zone. phytoplankton blooms in Lake Victoria were more severe in 2009 and after 2015. From the figure, we can visually get the relationship and spatiotemporal change characteristics between the phytoplankton bloom situation in Lake Victoria and the WPC around Lake Victoria in a long period of time. In 2000, the phytoplankton bloom in Lake Victoria was mainly concentrated in the west side, and the eutrophication degree of the lake was not high compared with that afterwards. In 2006, there was an obvious increase in phytoplankton bloom inside the lake, which was mainly concentrated in the northern and northeastern of Lake Victoria, and the WPI of the northeastern buffer zone was obviously weaker compared with that of other areas. The WPI of the northeastern part of the buffer zone was significantly weaker than that of other areas. During the period 2006-2015, the eutrophication degree of Lake Victoria was high, and the ecological environment was obviously affected. It is not difficult to see that domestic sewage and industrial wastewater generated by anthropogenic activities have seriously damaged the water quality of Lake Victoria, and the WPI of the surrounding areas has been significantly reduced. In 2021, the phenomenon of phytoplankton bloom was still serious, and the ecological protection and sustainable development of the area was still in danger of collapse. The ecological conservation and sustainable development of the region urgently needs the attention of the local government. In general, the areas with frequent phytoplankton blooms were in the northern and northeastern of Lake Victoria, where WPI of these areas was weaker. The spatial distribution of phytoplankton blooms can verify the accuracy of the mapping.

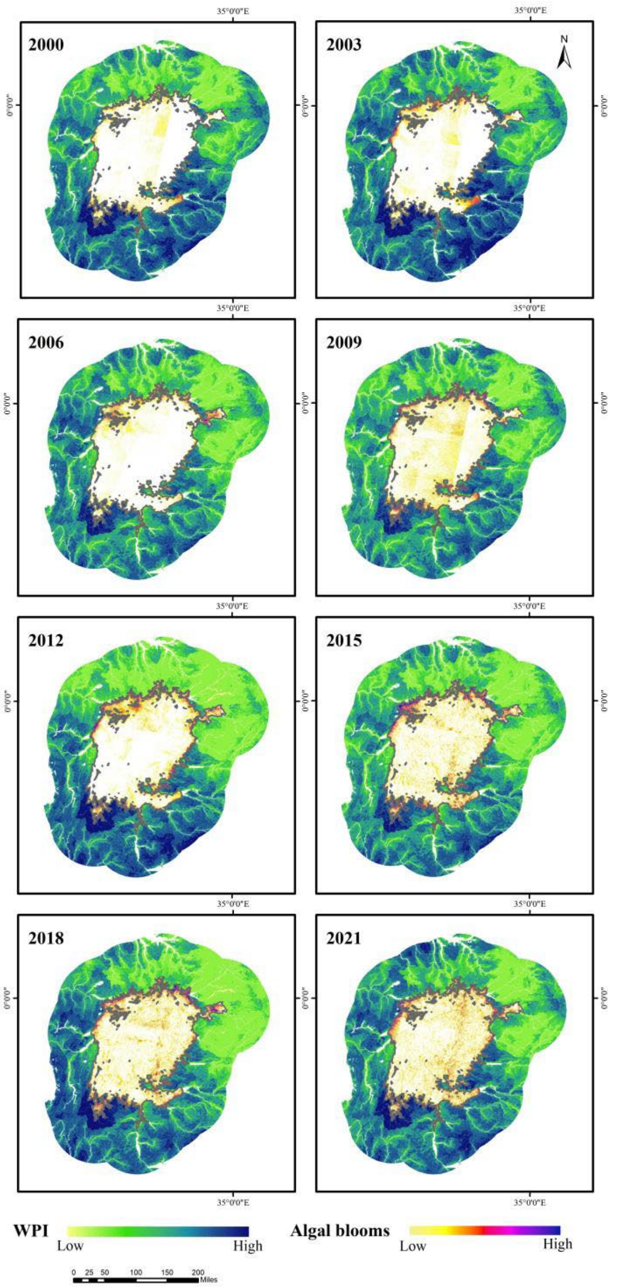

Figure 6. Phytoplankton blooms in Lake Victoria and WPI of its buffer zone.

4.3.2 Correlation analysis of economy and population with WPI

We discussed the correlation between two anthropogenic factors, socio-economic and demographic, and WPI in different regions (Table 2). The results showed a significant negative correlation between WPI and GDP in the study area (-0.750). The Spearman correlation coefficient of Kenya reached -0.821, while that of Uganda was only -0.286. However, the correlation between population and WPI was not high (-0.494), and even Uganda 's correlation coefficient is positive. This showed that economic development affected the ecological health around Lake Victoria and weakened the ability of the land to purify water. In turn, population increases can burden ecosystems.

WPI in different areas	Human activity indicators	
	GDP	Population
Kenya	-0.821*	-0.381
Tanzania	-0.571	-0.567
Uganda	-0.286	0.143
Study Area	-0.750*	-0.494

Table 2. Spearman correlation coefficient of WPI with GDP and population

5. Conclusion

Under the continuous threat of global sustainable development, quantitative evaluation of WPC and analysis of the relationship between anthropogenic activities and WPC are of great significance for strengthening the protection and rational utilization of water resources. In this study, we used the InVEST model to map the spatial distribution data of WPI in a long time series with high resolution around Lake Victoria from 2000 to 2021, and analyzed the spatial and temporal characteristics of WPI at multiple scales. The study also explored the relationship between phytoplankton blooms, socioeconomics and population and WPI. The study showed that 1) the total N/P in the study area had basically the same trend, but the retention and export of N were significantly greater than P; 2) There were significant spatiotemporal changes of WPI, with a general trend of initial decline followed by subsequent increase being observed. WPI is affected in areas near rivers and lakes. In terms of countries, Uganda had the weakest WPI overall, and Kenya had the strongest; 3) Domestic and industrial wastewater from anthropogenic activities seriously damaged the water quality of Lake Victoria, and phytoplankton blooms worsened year by year from 2000-2021, with a significant decrease in the WPI of the surrounding areas; 4) The WPI of the study area showed a significant negative correlation with GDP (-0.750), whereas the correlation with population correlation was not high (-0.494). In this study, high-resolution mapping and human impact assessment around Lake Victoria were completed using multi-source remote sensing data. The results of this research are important for water environmental protection and promotion of sustainable regional development, and can provide data support for local governments.

In further research, the assessment framework of WPI can be optimized in two ways. On the one hand, by improving the accuracy of the land use data in the InVEST model, the accuracy of the N/P output and retention can be improved. This can improve the resolution of the spatial distribution data of WPI and enable analysis at finer scales. On the other hand, when constructing the WPI, parameters related to anthropogenic activities and land properties can be introduced, making the quantitative calculation of WPC more accurate.

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