



What is the relationship between land use and surface water quality? A review and prospects from remote sensing perspective

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Abstract

Good surface water quality is critical to human health and ecology. Land use determines the surface water heat and material balance, which cause climate change and affect water quality. There are many factors affecting water quality degradation, and the process of influence is complex. As rivers, lakes, and other water bodies are used as environmental receiving carriers, evaluating and quantifying how impacts occur between land use types and surface water quality is extremely important. Based on the summary of published studies, we can see that (1) land use for agricultural and construction has a negative impact on surface water quality, while woodland use has a certain degree of improvement on surface water quality; (2) statistical methods used in relevant research mainly include correlation analysis, regression analysis, redundancy analysis, etc. Different methods have their own advantages and limitations; (3) in recent years, remote sensing monitoring technology has developed rapidly, and has developed into an effective tool for comprehensive water quality assessment and management. However, the increase in spatial resolution of remote sensing data has been accompanied by a surge in data volume, which has caused difficulties in information interpretation and other aspects.

Keywords Remote sensing · Land use · Water quality

Abbreviations

SDGs	The United Nations Sustainable Development Goals
COVID-19	Coronavirus disease 2019
RS	Remote sensing
GPS	Global Positioning System
SWAT	Soil and Water Assessment tool

GWR	Geographically weighted regression
DOM	Dissolved organic matter
TN	Total nitrogen
TP	Total phosphorus
BOD	Biochemical oxygen demand
COD	Chemical oxygen demand
SS	Suspended solid
MODIS	Moderate-resolution imaging spectroradiometer
MERIS	Missouri Emergency Resource Information System
IRS	Indian Remote Sensing Satellite
LISS	Linear imaging self-scanning
TM	Thematic mapper
ETM +	Enhanced thematic mapper plus
ENVISAT	Environmental satellite
ALOS	Advanced land observing satellite
PRISM	The Panchromatic Remote-sensing Instrument for Stereo Mapping
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
SPOT	Systeme Probatoire d'Observation de la Terre
HRGs	Geometry of high-resolution imaging device

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Highlights

- Different land use types have different impacts on water quality.
- Different spatial resolutions of remote sensing data have different application scenarios.
- Different statistical methods have their own advantages and limitations.

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HRS	High-resolution three-dimensional imaging system
VGT	Vegetation detector
MSI	Multispectral instrument
PCA	Principal component analysis
RA	Redundancy analysis
ERA	Extended redundancy analysis
CRA	Copula-based redundancy analysis
SLM	Spatial lag model
SEM	Spatial error model
LM	Lagrange multiplier
OLS	Ordinary least squares
PLS	Partial least squares regression
HSAs	Hydrological sensitive areas

Introduction

Healthy water quality is essential for sustainable agricultural production, human health, and ecological habitat stability (Riseng et al. 2011; Samways 2022). The availability and quality of water resources are related to the sixth envisaged goal (ensure access to water and sanitation for all and its sustainable management) of the United Nations Sustainable Development Goals (Huang et al. 2021; van Vliet et al. 2017). The deterioration of surface water quality has become a global environmental problem, especially during the coronavirus disease 2019 (COVID-19), which has not been fully controlled (Chu et al. 2021). Improving the surface water quality is the top priority to effectively recover the global economy and realize social sustainable development (Sivakumar 2021; Somani et al. 2020). Water quality degradation can be attributed to many influencing factors, such as climate change, vegetation cover, river topography, and land use in catchment areas (Poff et al. 2006; Rodrigues et al. 2018; Williams et al. 2015; Zieliński et al. 2016). Land use has become the core part of many international policy discussions (Bayer et al. 2017). There are many studies on assessing and quantifying the relationship between surface water quality and land cover and land use change patterns (Camara et al. 2019; Carey et al. 2013). In the past 60 years, nearly 1/3 of the global land area has changed, and about 3/4 of the land surface has been altered by human beings (Winkler et al. 2021). The spatial distribution of water quality reflects the process of human social and economic activities and determines the surface hydrothermal and mass balance, and its change directly affects the biogeochemical cycle and alters the water, energy, and carbon cycles of land and atmosphere, leading to climate change (Ni et al. 2021).

Understanding how land use affects water quality is essential to ensuring human well-being quality affects each other which has been a research focus (Rimer et al. 1978; Wagner et al. 2019). Early studies often simply linked the health of a

water body to the land use component of the watershed (e.g., percentage of land use) (Crosbie and Chow-Fraser 1999; Donohue et al. 2006). In addition to the influence of natural environment, including climate, water transparency, and water level changes, water environment is closely related to human activities. People's land production and living activities (Wang et al. 2016) have a profound impact on the material input process of surface, river, and lake ecosystems. In the meantime, the landscape pattern of land use will also affect the surface runoff, biological cycle, and geochemical cycle process, so that pollutants entering rivers and lakes have significant impact on water quality (Wagner and Fohrer 2019). For instance, studies near sampling sites examined the effect of human use and transformation of the land on water quality (Manfrin et al. 2016) and confirmed the helpful impact of forests on water quality. Urban housing and agricultural-related land use are mainly related to negative impacts on the overall quality of surface water (Manfrin et al. 2016; Zhang et al. 2010). Land use change has a series of profound impacts on ecological process, surface runoff, and hydrological cycle, thereby affecting river water quality safety (Guo et al. 2021). As a result, determining water quality does require attention to human land use activities. To discuss the issue of how land use and water quality affect each other is of great significance to land use management planning and effective protection of water ecological environment resources. In addition, it has been shown the critical value of local land planning and utilization in assessing watershed ecological water quality (Damanik-Ambarita et al. 2018). Previous studies noted that the number of nitrogen, phosphorus, and fecal coliforms increased in farming area in Upper Okoni Basin, Georgia (Fisher et al. 2000). Therefore, changing land use patterns leads to changes in runoff (Zhou et al. 2019), surface water supply output (Wu and Haith 1993), and water quality (Zhang et al. 2019), which is considered to be one of the main factors that change the hydrological system (Bateni et al. 2013; Jordan et al. 1997). Impervious urban land surfaces such as residential land, public facilities land, industrial land, and cement pavement boost stormwater runoff by reducing downstream bare soil volume (Damanik-Ambarita et al. 2018; Estes et al. 2009). Increased nitrogen and phosphorus inputs in farmland and construction land are the main cause of eutrophication (Broussard and Turner 2009; Karmakar et al. 2019, Paul and Meyer 2001).

Comprehensively, scientific consideration of water quality influences is essential to the implementation of effective river management strategies. Land use is often evaluated through field observations (Erba et al. 2015), satellite remote sensing, and "3S" technology (Geographic Information System (GIS); remote sensing (RS); Global Positioning System) (Leps et al. 2015). In recent years, in "Land use-Water quality" assessment using remote sensing data sources and "3S" technology,

building and farmland (Du et al. 2018; Schmalz et al. 2015; Smucker and Detenbeck 2014). In the context of decreasing arable land area and decreasing fertility, humans apply excessive amounts of pesticides and fertilizers to maintain crop growth rates and yields, which leads to increased intensity of arable land use and negative effects on regional water and environmental health (Chen et al. 2021). Rapid global changes including urbanization, population, socio-economy, energy demands, and climate have put unprecedented pressure on water resources and the associated systems. In response to population growth around the world, humans have built a large number of hydraulic structures to supply irrigation power and water resources (Bertone et al. 2016; Strehmel et al. 2016; Lu, 2020), yet in recent years the exponential growth of light and heavy industries around the world has consumed large amounts of water resources (Courtonne et al. 2016; Kosolapova et al. 2021). With the analysis of published research (Table 1), we found that among the many studies on the relationship between land use types and water quality, the three land use types of agricultural land, forest

land, and urban land have the highest frequency, so this paper focuses on these three land use types.

As shown in Fig. 2, we found that agricultural land and construction land have severe great negative impact on the water environment in general, while forest land was considered to have a less detrimental effect on surface water quality. In small-scale buffers, agricultural land usually brings relatively large adverse impact on water quality, but in large-scale buffers, agricultural land has some improvement on water quality. Forest lands are often considered to be a barrier to water quality degradation effect to a certain extent. Construction land is the concentrated area of human activities. With the increase of buffer zone, impervious surface runoff also increases. Industrial wastewater and domestic sewage discharge cause certain pollution to the water environment. The use of pesticides and fertilizers is the main factor of pollution to the water environment in agricultural land uses. In the small-scale buffer zone, nitrogen, phosphorus, and other elements are less absorbed by the soil in the migration process, resulting in a large

Table 1 Impact of different land use types on water quality

Reference	Land use types						
	Agricultural	Urban	Forest	Grassland	Meadow	Bare land	Other
White (1976)	✓	✓					
Richardson (1979)	✓						
Oakes et al. (1981)	✓						
Nichol (1993)	✓	✓	✓	✓			
Mattikalli and Richards (1996)	✓				✓		
Jordan et al. (1997)	✓						
Rai and Sharma (1998)		✓	✓				
Perry et al. (1999)			✓				✓
Roman et al. (2000)		✓					
Sliva and Williams (2001)	✓	✓	✓				
Tong and Chen (2002)	✓	✓					
Little et al. (2003)	✓					✓	
Ngoye and Machiwa (2004)	✓	✓	✓	✓			
Pintar et al. (2006)		✓					
Li et al. (2008)	✓	✓					
Eugene and Rabalais (2009)	✓						
Singh et al. (2010)	✓	✓	✓				
Tu (2011)	✓	✓	✓				
Carroll et al. (2013)	✓	✓	✓				
Ding et al. (2015)	✓	✓	✓				
Chen et al. (2016)	✓	✓	✓				
Hua (2017)	✓	✓					
Melland et al. (2018)	✓				✓		
Liu et al. (2018)		✓	✓	✓			
Kondraju and Rajan (2019)	✓	✓					
Song et al. (2020)		✓					
Qiao et al. (2020)	✓	✓	✓				

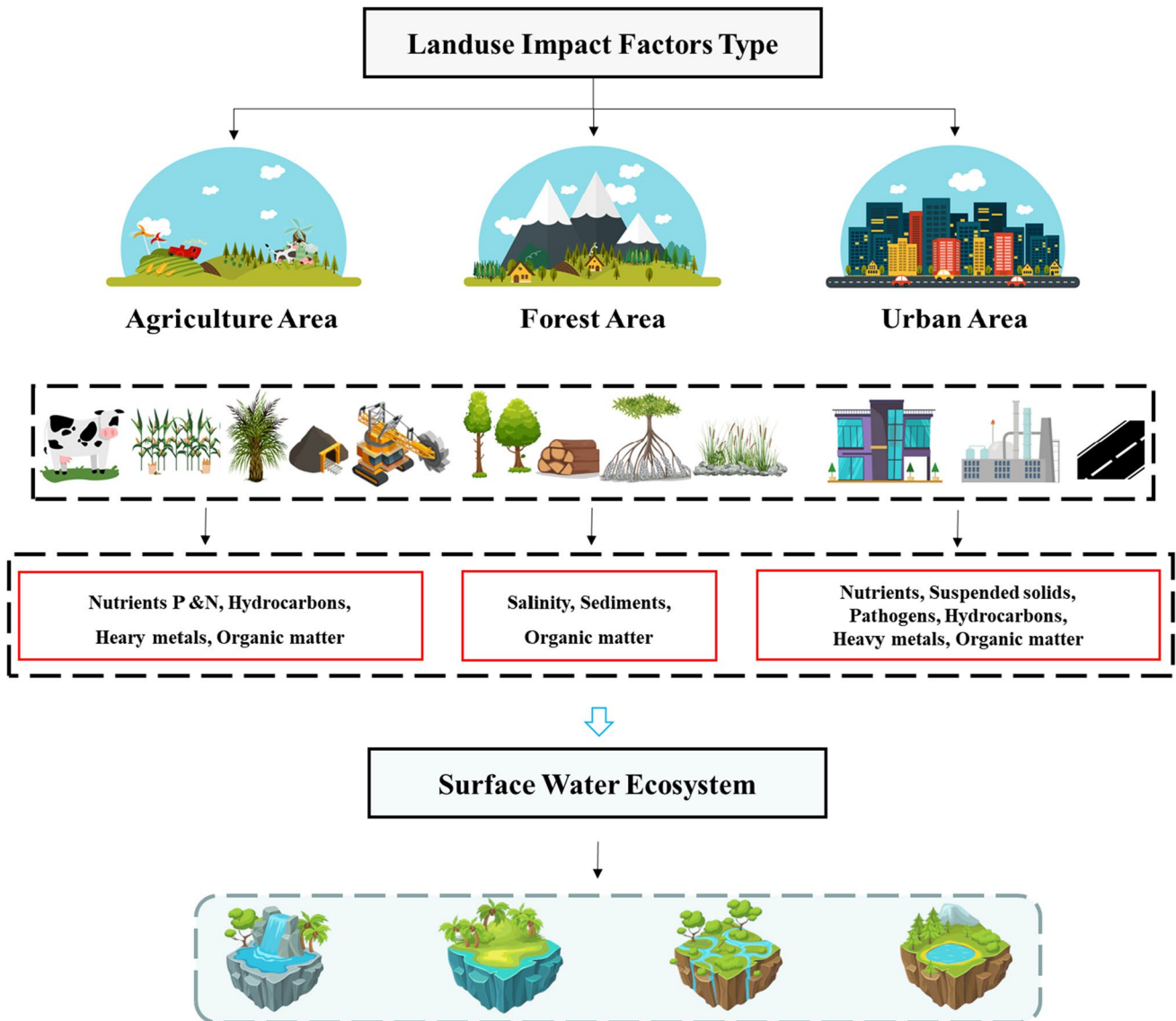


Fig. 2 Influence mechanism of land use on water quality

number of pollutants directly entering the water body in a short time.

Impact of agricultural land on water quality

Stoate et al. (2009) claimed that agricultural land does negatively affect water quality which comes from planting, application inputs (fertilizers, agricultural chemicals), and agricultural irrigation. Many studies have shown that with the increase of agricultural land area and the decrease of water quality, habitat and biological combination, row crops, and other forms of intensive planting have a strong impact on river conditions (Dillon and Kirchner 1975; Wang et al. 2019a). It has been shown that as more land is reclaimed for agriculture, sediment, dissolved organic matter (DOM), total

nitrogen (TN), and total phosphorus (TP) yields in surface water bodies in the area will increase (Ni et al. 2021). The ecological quality of highly agricultural rivers tends to be poor as evidenced by a decline in various ecological indices and riparian stability (Lacher et al. 2019). Previous studies in many countries have found that watersheds with a large proportion of farmland can emit more nitrogen and phosphorus (Gu et al. 2015; Neill 1989). Nitrogen and phosphorus fertilizers are often applied in large quantities during the growth of crops, and the phosphorus fertilizers that are not absorbed by crops are flushed into rivers by rainfall splashing, water infiltration leaching, and runoff, which in turn cause nitrification and denitrification reactions between different forms of nitrogen (Camara et al. 2019; Jaworski et al. 1992; Li et al. 2020). The large increase in dissolved organic

carbon export from the region's rivers has been associated with the expansion of agricultural land area, but few scholars have quantified how land use affects organic carbon transport, concentration, and quality (Guzha et al. 2018; Wilson and Xenopoulos 2009). In addition, excessive nitrogen and phosphorus in farmland enter the water through runoff, and the increase of these nutrients accelerates eutrophication, leading to the decrease of microorganisms, algae, aquatic higher plants, and various invertebrates and vertebrates (Yang et al. 2020).

Although there are uncertainties in measuring and predicting the impact of farmland and agricultural activities, we have learned unequivocally that agricultural production does lead to an increase in nutrients in the region's waters, thereby accelerating eutrophication in the waters. Excessive application of chemical fertilizers and pesticides can also be harmful to water quality; for instance, the increase of pesticide and fertilizer application was associated with the increase of nutrient emissions and the extinction of underwater aquatic vegetation in the Mississippi River (Turner and Rabalais 1991), the Chesapeake Bay Basin (Boynton et al. 1982; Kemp et al. 1983), the Odense Fjord catchment (Molina-Navarro et al. 2018), and the Chaohu lake basin (Yang et al. 2020). In 1981, British scholar OAKES et al. explored and studied the distribution of solute extracted from farmland in major aquifers in the UK from 1975 to 1980 and concluded that nitrate concentration was significantly correlated with agricultural production practices (Oakes et al. 1981). Agricultural nonpoint source pollution is now widely recognized as a critical nutrient input to surface waters due to sources of intensive fertilizer applications (Huang et al. 2021). Improper agricultural practices, such as over-tillage, result in the destruction of soil particles and the flow of sediment into surrounding water bodies through surface runoff (Hu et al. 2019). Scholars have also found that untreated agricultural wastewater was discharged directly from intensively cultivated rice farmland into environmental surface water bodies, leading to further deterioration of water quality (Minh et al. 2020).

The proportion of animal husbandry in agriculture is much higher than planting in some regions. Livestock excrement contains large amounts of nitrogen, phosphorus, and other fertilizer components, and livestock barn sewage may be discharged directly into rivers, lakes, and other water bodies (Samways 2022). In addition, the accumulation of manure in the field and the storage of livestock barn sewage in ponds can cause water pollution through surface runoff and underground seepage of rainwater (Cesoniene et al. 2019). In summary, the combined results show that there is a significant negative correlation between agricultural land use and agricultural production activities and surface water quality compared to forest land and urban land use. For example, in Thailand, the relationship between water quality

of the Menghe River and agricultural land (especially paddy field) in the basin is the most significant, and biochemical oxygen demand (BOD) and TP contents are significantly positively correlated with the proportion of agricultural land area, indicating that agricultural land plays a "source" role in the pollution load of BOD and phosphorus in river water (Tian et al. 2020). Farming is the key source of nitrogen and phosphorus pollution in the Pearl River Basin, followed by urban sewage, aquaculture, and rural sewage. The study of Taihu Lake Basin and Honghu Lake Basin with the highest proportion of agricultural land showed that the output capacity of TN, TP, chemical oxygen demand (COD), Cr^+ , and other pollutants from forest land, urban land, and agricultural land has increased significantly (Li et al. 2020). To stop the continuous deterioration of water quality, local people may actively regulate the ecosystems of water bodies such as rivers at the expense of productive agricultural land (Mishra et al. 2021; Trodahl et al. 2017).

Impact of urban land on water quality

Water quality degradation is most typical in areas with more pronounced human activity and rapid land use change, especially in areas experiencing rapid urbanization. With continuous rapid growth and urbanization, the rapid expanding construction land area and industry exert great impacts on the eco-landscape, water, and the soil (Dewan and Yamaguchi 2009; Lacher et al. 2019). Pollution concentrations have a direct impact as nutrients, metals, medicines, and toxic substances invariably end up flowing into rivers. In general, rapid urbanization often results in significant regional land use/cover changes, mainly in the form of increased impervious surfaces (Delphin et al. 2016; Wang et al. 2020). Impervious surfaces cause changes in many ecological processes, such as increased surface runoff, increased soil erosion, and increased non-point source pollution, which is one of the main factors contributing to the deterioration of the water environment (Lin et al. 2020). If the percentage of impervious surface in an area reaches 10–15%, then river water quality and common pollutants in aquatic ecosystems, such as nitrogen, phosphorus, and heavy metals, will increase significantly, leading to a decline of water body health (Brabec et al. 2002; Dong et al. 2020; Klein 1979; Tasdighi et al. 2017). This particular land use will primarily result in negative water quality impacts, which negatively affect water resources by increasing runoff and facilitating the dispersion of nonpoint source pollutants (Li et al. 2018; McGrane 2016).

As urbanization accelerates, the natural landscape is destroyed and modified, and peak flows and runoff subsequently increase dramatically, changing the spatial and temporal patterns of surface runoff and the hydrological cycle processes in urban areas and affecting the water

balance within the region (Han and Jia, 2017; Pankaj, 2021). Due to the differences in sewage treatment technology and nutrient removal efficiency, sewage discharge may also lead to spatial and temporal changes in nutrient fluxes in urbanized basins. This heterogeneity results in differences in the effects of land use types within different catchment units on water quality (Fashae et al. 2019; Hale et al. 2015; Xian et al. 2016). Heavy rains and other events in urban areas often lead to a large amount of water rapidly passing through the watershed carrying with it more nutrients, sediments, and pollutants (Zhao, 2018). Rivers and rivers in densely populated drainage areas usually have high solute levels, including nitrogen and phosphorus (Marti et al. 2004; Lu 2020). In urban areas, point pollution sources, such as sewage farm, have caused huge amounts of nutrient load for receiving waters (Xian et al. 2019). In studies that recognize and understand how land use practices impact water quality, larger effluent loads may be a confounding factor for other land uses.

Like agricultural land, urban land is generally considered to be a key contributor to water quality changes in watersheds (Shi et al. 2017; Pankaj, 2021). Human behaviors associated with urbanization (e.g., increased industrialization and housing development) can affect the water quality of regional surface water bodies. Therefore, the consistency of land use types in urban areas is one of the focal points of water quality research concerns. Some relationships are difficult to explain as many parameters, including water storage capacity, evapotranspiration, interception, runoff, and emission, are related to the fate and erosion mode of water pollutants. At the same time, large amounts of industrial wastewater and domestic sewage generated by human activities in dispersed urban areas exacerbate water degradation (Ding et al. 2016; Dong et al. 2020), which reflects that with the improvement of population, economy, and urbanization in the basin, the sewage collection and treatment facilities in the dispersed urban areas have not kept up with the expansion speed and scale of the city and population, causing serious pressure on river water quality. Moreover, the construction of reservoirs and dams to meet the demand of urban population's water consumption has not only changed the water resources storage in the basin and reduced the efficiency of water resources utilization, but also affected the natural degradation process of pollutants (Lu 2020). Harmful substances that should have been naturally degraded in wetlands and rivers are stored, multiplied, and fermented in artificial dams, leading to deterioration of water quality (Xu et al. 2020). Thus, urban construction has put lots of pressure on China, which has a severe shortage of water resources per capita, and artificial efforts to change the spatial and temporal distribution of water resources are counterproductive.

Impact of forest land on water quality

Due to the fixation and adsorption of pollutants by forests, which serve as sinks for river nutrients, the total phosphorus and total nitrogen levels in the watershed tend to decrease as the area of forested land increases. Since terrestrial vegetation absorbs bioavailable phosphorus, the soil nutrient level in the basin may decrease. In accordance with the age and type of vegetation, the assimilation rate of nutrients may be different. Forests are more effective in removing nutrients from basin soils than shrubs and grasslands because their leaves and roots are more developed (Lintern et al. 2018). Many studies have shown that after rainwater passes through the forest canopy layer, the content of its chemical composition changes significantly through the canopy exchange (Jachniak et al. 2019). For example, the showering of rainwater on the surface exudates of plant bodies and the absorption of rainwater ions by branches and leaves, as well as the washing of solid sediments such as dust and particles on the surface of branches and leaves by rainwater, cause changes in the content of nutrients in the penetrating rain and trunk stem flow (Rolando et al. 2017; van Dijk and Keenan 2007; Vermaat et al. 2021). However, afforestation may also cause diffuse pollution in the process of building and managing forest land (Duffy et al. 2020). Although nutritive materials are usually applied to nutrient-poor soil areas at the time of the initial afforestation, the impact of its applications is generally weaker than agricultural land (Wang et al. 2021).

Some woodlands obviously have purification effect, examples including riparian forest, alluvial forest, and hedgerow farmland (Ranjit and Puneet 2019; Gong et al. 2021). Riparian forests and forest roots have filtration and capture nutrients such as nitrogen, potassium, phosphorus, and metallic element (Jachniak et al. 2019). Generally, woodland is considered a “sink” landscape with pollutant interception function, which can reduce the negative impact of non-point source pollution on water quality (Cecilio et al. 2019). Compared to non-forested land and farmland watersheds, the soil of forested land also has a good agglomerate structure and is more conducive to microbial growth, and the leaf litter layer of the forest makes the forest ecosystem a powerful purifier of atmospheric rainfall (Xu et al. 2021). Thus, maintaining a large distribution of forestry land, aggregation, and good connectivity in the basin with strong control effects, control of pollutants entering the river, and the distribution of forestry land in the riparian zone (below 100 m) are all important factors in maintaining good river water quality (Townsend et al. 2012, van Dijk and Keenan 2007).

Consistent with studies emphasizing the ability of woodlands to reduce nutrient and sediment content in regional water bodies (Ranjit and Puneet 2019), many studies have revealed a positive relationship between forest cover and

water quality. Forests are generally considered to be helpful to protect land, facilitate infiltration, reduce rapid surface flow, and limit sediment flow and turbidity. Considering some land with high carbon stock and associated phosphorus transform risks (Rolando et al. 2017), we found that interactions between carbon land and forest land may be related to a broad European context. The Irish Forestry Service has adapted its environmental protection regulations in recent years to reduce the potential impacts of afforestation in hydrologically fragile areas, including the management of acid-sensitive and low production sites. In combination with other measures, this has led to a reduction in arable land requiring nitrogen and phosphorus inputs (especially peat) during major changes in afforestation or drainage (Ding et al. 2016; Jachniak et al. 2019).

Influence of land use on water quality change from the perspective of remote sensing

Since the 1970s, satellite remote sensing data has become popular for land use and water resource management, as it provides an effective tool for comprehensive water quality and land use assessment and management. The size of the most detailed unit that can be identified on a remotely sensed image is usually expressed in spatial resolution, which is an indicator of the detail of surface targets through image resolution. The size of spatial resolution reflects the level of spatial detail and the ability to separate it from the background environment (Zhang et al. 2020). Different satellite data sources (Images with different spatial resolutions) have different sizes of meaningful units that can be identified. In other words, their primitive scales are different. This is because the spatial resolution of each target on the images does not depend totally on the absolute size of its resolution and is related to its contour, size, relative brightness, and structure with respect to surrounding objects (Gong et al. 2006). For example, in the land cover classification of remote sensing images, fine spatial resolution can reduce the boundary mixing elements and improve the classification

accuracy to a certain extent; however, higher resolution may lead to an increase of spectral variability within the category and thus reduce the classification accuracy. Current scholars use satellite remote sensing images to monitor water quality parameters of surface water environment, such as turbidity, salinity, chlorophyll concentration, TN, TP, BOD, COD, SS (suspended solid), and DOM. In addition, remote sensing images of different spatial resolutions can also be used to monitor and classify land use patterns and surface cover types at different scales.

As shown in Table 2, the lower the spatial resolution, the more the number of mixed pixels. The larger the area of mixed pixels is, the more serious the leakage is and the more inaccurate the interpreted water body is. Excessive spatial resolution will cause too much detail information, interfere with the resolution of water, and increase the amount of data and workload, which is not conducive to the extraction of water information (Ming et al. 2008). In addition, in regions with flat terrain, regular boundaries, and large water area, the influence of spatial resolution on the extraction effect is smaller (Fisher et al. 2018). In areas with rugged terrain, blurred boundaries, and small water area, the error of water extraction results increases with the decrease of spatial resolution. For different applications, when selecting the spatial resolution of images, it is necessary to comprehensively consider the accuracy requirements, economic costs, labor costs, and time costs (Chen et al. 2021; Zhang, 2016).

Application of high-spatial-resolution remote sensing data

When the spatial resolution of the images reaches the meter level, most of the surface targets such as tree, car, road, and house will appear precisely on the image. With the outstanding high spatial resolution, high-definition remote sensing images can realize fine earth observation and obtain geometric structure, texture size, spatial layout, and other characteristic information of feature targets, with good conditions and foundation for interpretation and analysis (Villegas and Torres 2020). However, how to make best use of the potential of more accurate spatial resolution

Table 2 Advantages and disadvantages of three spatial resolution

Spatial resolution	Advantages	Disadvantages
High	(i) Exactitude earth observation (ii) Better representation	(i) Large amount of data, complex spectral information, low separability (ii) “Homogeneity and Heterogeneity”
Moderate	(i) High data volume and variety (ii) Mature interpretation technology (iii) Convenient access	(i) Interpretation accuracy is easily affected (ii) Classification accuracy is not high (iii) Mixed pixels exist for images
Coarse	(i) High temporal resolution (ii) Global coverage (iii) Continuous observation	(i) Poor spatial consistency (ii) Low spatial detail (iii) Weak feature recognition

capability is important to improve the classification precision and velocity of target extraction (Gong et al. 2006). At present, scholars have accelerated the application of high-resolution images, especially high-spatial-resolution images, in urban environment, precision agriculture, transportation and road facilities, forestry measurement, military target recognition, and disaster assessment (Zang et al. 2021). People often choose data because of the limitation of the scale or resolution of existing data. Multispectral and high-spatial-resolution datasets are growing in number (IKONOS, QuickBird, GeoEye-1, WorldView-1/2, GF-2, etc.); selecting the proper data from multiple data sources has become a new challenge in many industries; e.g., forest monitoring (Zhang et al. 2020), land use survey (Fisher et al. 2018), and other fields have gradually replaced low- and medium-resolution remote sensing data and become the preferred data source for research (Chen et al. 2011). Under the background of increasing similar remote sensing data, how to find suitable remote sensing data to meet the application requirements has become a subject worthy of study. For a specific application, remote sensing data with different basic quality parameters have different application potential. Many scholars have used IKONOS, QuickBird, and WorldView series data to extract information of urban water bodies, land use types, mangroves, and vegetation tree species. The results of those studies show that high-resolution data have higher accuracy in extracting information (Alphan and Celik 2016). Therefore, researchers often use a basic quality parameter of remote sensing data to uniquely determine the application potential of high-spatial-resolution remote sense datasets (Villegas and Torres 2020).

As the observation scale becomes finer and objects become more detailed, the complexity of objects increases rapidly, which leads to increased intra-class variability while reducing inter-class differences; creates more challenges for classifying; and extracts information from images (Zang et al. 2021). The spectral resolution of high-spatial-resolution remote sensing image is relatively low and contains a lot of detail information, making the spectral distribution very complex and reducing the identifiability of features in the spectral bands. The difference of spectral information of similar ground objects increases, and the spectral information of different ground objects overlaps with each other, making the intra-class variance larger and the inter-class variance smaller and resulting in a large number of “Homogeneous Heterogeneous” and “Homogeneous Heterogeneous” phenomena, which greatly reduces the classification accuracy of images (Gong 2006). The application potential of higher spatial resolution remote sense datasets is often affected by multiple basic quality parameters of the data, which is the result of the interaction of multiple basic quality parameters (Sekrecka and Kedzierski 2018). The application potential of remote sensing data is simply defined by the corresponding basic

quality parameters of remote sensing data. The information provided by high-resolution satellite images is composite, complex, and diverse. There is no clear cognition and guidance for data applications, making it difficult for data users to better select remote sensing data products that are suitable for specific applications (Wang et al. 2020). Researchers can only qualitatively give the conclusion of whether the data can meet its application but cannot further explain to what extent the data can meet the application requirements. Therefore, it is necessary to comprehensively consider the correlation between basic quality parameters and then build an application-oriented application potential evaluation model of higher spatial resolution remote sense datasets to predict the application potential (Peng et al. 2019).

Application of medium spatial resolution remote sensing data

In remote sensing applications, the spatial resolution of 10–120-m satellite data is generally considered medium resolution data. Although the spatial and temporal resolution of remote sensing images has been improved to a certain extent, high-resolution remote sensing images have also been widely used in many ways, but the medium-resolution remote sensing images are still the main data source of research and application because of convenient access and relatively mature interpretation technology. The classification accuracy is not high because the accuracy of medium-resolution image interpretation is affected by spatial resolution, spectral characteristics of ground objects, and other factors (Ouma 2016). The field survey data with high accuracy can only obtain data in some areas due to data confidentiality and cost, making the data difficult to obtain in many applications and research. Overall, the computer classification accuracy of medium-resolution remote sensing images is relatively low, and the classification results are suitable for medium-scale applications and research, such as land use cover, plant communities, forest pests and diseases, flood disaster assessment, and carbon sources/carbon sinks, but not for micro-applications and research with high accuracy requirements such as land use change monitoring and engineering design in smaller regions (Estoque et al. 2015).

Mixed pixels mainly refer to the type of ground objects in a certain pixel that is not single, and there are different types of ground objects. Mixed pixels are mainly distributed at the boundary of the ground class. As the brightness value of mixed pixels is not close to any representative category, it is easy to cause classification error. Undoubtedly, the existence of mixed pixels in medium-resolution remote sensing image is a key factor affecting the classification accuracy, especially in the classification and recognition of linear and fine ground objects, which are difficult to identify. In the process of interpretation and classification of land use types,

the problem of mixed pixel is often encountered (Phiri et al. 2020). To solve this problem, the weight of ground objects in mixed pixel can be converted by certain methods, and then the weight of actual ground object area can be judged. When the spatial resolution is too low, there are more mixed pixels in the image, and the computer classification accuracy is relatively low. However, it may be due to data requirements and computational limitations, or satellite instruments (especially those publicly available) that prioritize spectral information (higher radiometric sensitivity) over higher spatial and temporal resolution. Therefore, it is not true that the higher the spatial resolution, the higher the value of the application (Goldblatt et al. 2017). If the spatial resolution is too high, the same type of region may be divided into multiple types of pixels. For example, if the resolution is greater than 2 m, the afforestation woodland in the construction land and the small woodland in the village are likely to be identified as vegetation, thereby reducing the classification accuracy. Therefore, the appropriate spatial resolution is the key to improve the automatic classification accuracy (Ouma 2016; Peng et al. 2006).

Application of coarse spatial resolution remote sensing data

Remote sensing data with large-scale and coarse spatial resolution has become an important data source in global change research because of its long-term continuous observation, high temporal resolution, and global

coverage. For example, Moderate-resolution Imaging Spectroradiometer 500 m/1000 m resolution data and Missouri Emergency Resource Information System production are often used for large-scale land use or water quality monitoring applications (Zhang et al. 2009). The low-spatial-resolution remote sensing data can also provide information to reflect the characteristics of surface, cloud, ocean color, phytoplankton, biochemistry, atmospheric temperature, and ozone. These characteristics allow significant advantages in the research fields of sea surface temperature change, and greenhouse gas monitoring. Geostationary satellites can obtain large-scale remote sensing data with ultra-high temporal resolution for their fixed observation areas, but they cannot cover polar regions, and polar orbit satellites can compensate for this shortcoming. Therefore, the remote sensing monitoring covering the world is not competent for a single platform or sensor; these low spatial resolution datasets have different data acquisition platforms, data acquisition strategies, and generation algorithms, resulting in poor spatial consistency between them. We can see from Table 3 that since 1998, most remote sensing studies on land use and water quality have focused on medium-spatial-resolution remote sensing studies, and most of them use Landsat remote sensing platform data series, while the number of remote sensing studies at low spatial resolution is very small.

Table 3 Researches from remote sensing perspective at different spatial resolutions (see the list of Abbreviations above for the full spelling)

Platform/source	Sensor	Pixel size (m)	Reference
IRS 1A/1B	LISS-II	36.25	Rai and Sharma (1998)
Landsat 4/5	TM	30/120	Perry et al. (1999)
Landsat 5	TM	30/120	Little et al. (2003)
Landsat 5/7	TM/ETM+	15/30/120	Zhao et al. (2004)
Terra/Aqua	MODIS	250/500/1000	Li (2004)
Landsat 4/5	TM	30/120	Li et al. (2008)
Terra/Aqua and ENVISAT	MODIS and MERIS	250/500/1000	Zhang et al. (2009)
IRS 1C	LISS-III	23.6	Singh et al. (2010)
ALOS	PRISM	2.5	Zhao et al. (2012)
Landsat 5/7	TM/ETM+	15/30/120	Huang et al. (2013)
Landsat 4/5	TM	30/120	Bu et al. (2014)
Terra	ASTER	15/30/90	Kawamura et al. (2015)
Landsat 5	TM	30/120	Chen et al. (2016)
Landsat 5/8	TM/OLI	15/30/100/120	Hua (2017)
Sentinel 2A	MSI	10/20/60	Kondraju and Rajan (2019)
SPOT 6	HRGs/HRS/VGT	1.5/6	Song et al. (2020)
Landsat 5	TM	30/120	Lei et al. (2021)

Conventional method of land use impact on surface water quality index

As the impact of land use/cover change on the ecological environment is intensifying, scholars at home and abroad have conducted studies on the comprehensive impact of regional land use change on the ecological environment. As a whole, the current research methods and steps are Data collection–Model building–Analysis–Prediction, to achieve a scientific and reasonable explanation of land use/cover change, its driving factors, and driving mechanisms (Damanik-Ambarita et al. 2018). As shown in Table 4, scholars mainly use geostatistical and mathematical modeling analysis methods to analyze the quantitative relationship between land use and water quality. In general, the impact of land use/cover change on ecological environment, especially on water ecological effect, has gradually gained attention, and the research direction has gradually shifted to the study of modern resources and environment, and combined with modern integrated disaster risk management research, but still mainly static research, dynamic simulation is not enough, and the lack of a unified index system, the research is not comprehensive and systematic (Lin et al. 2014).

Correlation analysis

Correlation analysis refers to the analysis of two or more variables that correlate to each other. Correlation analysis originated, which is also the beginning of statistics (Gibbons and Chakraborti 2014). Correlation analysis addresses the following two issues: determining the statistical association between two or more variables; and if an association exists, further analyzing the strength and direction of the association. The Pearson correlation coefficient, known as the product difference correlation coefficient, is the most commonly used correlation coefficient, which takes a value from -1 to 1 . The larger the absolute value, the stronger the correlation. The coefficient is calculated and tested as a parametric method and is suitable for correlation analysis of continuous variables.

The Pearson correlation coefficient is defined as the quotient of the covariance and standard deviation between the two variables (Sorana and Lorentz 2006):

$$\rho_{X,Y} = \frac{\text{cov}(X, Y)}{\sigma_X \sigma_Y} = \frac{E[(X - \mu_X)(Y - \mu_Y)]}{\sigma_X \sigma_Y} \quad (1)$$

The above equation defines the overall correlation coefficient, where ρ is often used as the representative symbol.

Table 4 Application of different analytical methods

Research method	Analysis method/model	Application example	Spatial scale
Correlation analysis	Spearman's correlation analysis; nonparametric Spearman rank correlation	Tu and Xia (2008), Ding et al. (2016) Fisher et al. (2018), Li et al. (2020)	Riparian zone, watershed, and sub-basin
	Analysis of variance	Sonoda et al. (2011), Ujoh (2014), Fashae et al. (2019)	
	Pearson's correlation	Kibena et al. (2014), Little et al. (2003), Chen et al. (2021)	
	Cluster analysis	Salahat et al. (2014), Wong (2005), Das et al. (2020)	
Regression analysis	Multivariate linear regression	Fashae et al. (2019), Giri et al. (2018) Chen et al. (2020), Zhang et al. (2020)	Riparian zone, river reach, basin, and sub-basin
	Multiple regression analysis	Woli et al. (2004), Zampella et al. (2007) Chen et al. (2020), Nie et al. (2011) Fadhil et al. (2021)	
	Spatial regression analysis	Babcock et al. (2013), Wang et al. (2017)	
	Multilayer perceptron model Stepwise multiple regression	Selle et al. (2008) Forsius et al. (2017), Ren et al. (2003), Chen et al. (2020)	
Redundancy analysis	Classical redundancy analysis	Li et al. (2018), Qiao et al. (2020), Wu et al. (2021)	Riparian zone, sub-basin
Mixed model analysis	Linear mixed model	Liu et al. (2013), Swaffer et al. (2018)	Riparian zone, river reach, basin, and sub-basin

Estimating the sample covariance and standard deviation, the sample correlation coefficient (sample Pearson coefficient) can be obtained, commonly expressed as r :

$$r = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2} \sqrt{\sum_{i=1}^n (Y_i - \bar{Y})^2}} \quad (2)$$

where \bar{X} and \bar{Y} are the sample mean for X_i samples.

Spearman correlation coefficient can be calculated even if the original data are rank information. Spearman's correlation coefficient can also be calculated for data that obey Pearson's correlation coefficient, but the statistical efficiency is lower than that of Pearson's correlation coefficient (Sorana and Lorentz 2006). Its formula is:

$$rho = \frac{\sum(x'_i - m_{x'}) (y'_i - m_{y'})}{\sqrt{\sum(x'_i - m_{x'})^2} \sqrt{\sum(y'_i - m_{y'})^2}} \quad (3)$$

here x' is rank(x), and y' is rank(y). It is defined as Pearson correlation coefficient between rank variables:

$$\rho = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2} \sqrt{\sum_i (y_i - \bar{y})^2}} \quad (4)$$

where x_i and y_i are the original variables. X_j and Y_i obtained by rank mapping. The mapping can be taken as the average of the descending position of each original data. Denote $d_i = x_i - y_i$. Its simplified formula is:

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \quad (5)$$

In practical problems, researchers often encounter problems in which multiple variables are studied, and in most cases, there is often some correlation between multiple variables. The large number of variables coupled with the correlation between them inevitably increases the complexity of analyzing the problem. The main issue is to find a way to synthesize a few representative variables from multiple variables, which can represent the majority of information of the original variables but are not correlated with each other and can be further analyzed statistically on the basis of the new combined variables, and this requires principal component analysis. Principal component analysis (PCA) is a multivariate mathematical analysis method that examines the correlation between multiple variables (Gniazdowski 2021; Zhang et al. 2011). For all the variables originally proposed, duplicate variables (closely related variables) were removed as redundant and as few new variables as possible were created so that these new variables were two unrelated and that these new variables maintained the original information as

much as possible in terms of reflecting the information on the subject (Paul and Meyer 2001). In river water quality studies, the potentially relevant variables describing water quality are divided into fewer mutually independent principal components (Diamantini et al. 2018).

Trend analysis is used when detecting elemental trajectories, and point source pollution is usually marked at a site and investigated using Spearman's rank correlation coefficient analysis. The "footprint" is produced by advection and dispersion processes, resulting in concentrations decreasing with extent of the source. This approach can also be considered for monitoring water quality or assessing the effectiveness of remedial measures. Spearman rank correlation coefficient has some advantages, such as it is a non-parametric technology, meaning it is not affected by the overall distribution (Siddique and Mukherjee 2017). This method does not require regular data collection because it has some capacity to accommodate abnormal data values. The limitations of Spearman rank correlation coefficient is that when the data is converted to rank sum, it will lose information. If the data is normal distribution, Spearman rank correlation coefficient is not as strong as PCA (Zhang et al. 2022).

Regression analysis

The idea of regression analysis is a mathematical algorithm to determine the correlation between variables by using mathematical statistics and a large number of observation data (Lindley 1991). This idea is often adopted in issues involving multiple factors and variables, such as economic issues and the cost of raw materials (Aldrin 1997). The regression analysis method can characterize the association between parameters by a mathematical expression. With a dependent variable Y and n independent variables X_1, X_2, \dots, X_n , the relationship between the dependent and independent variables can be expressed as in Eq. (6) (You and Yan, 2017):

$$Y = a_0 + a_1 \cdot X_1 + a_2 \cdot X_2 + \dots + a_n \cdot X_n + \varepsilon \quad (6)$$

where $a_0, a_1, a_2, \dots, a_n$ are constants, and ε is the error coefficient.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k \quad (7)$$

where y denotes the dependent variable. x_1, x_2, \dots, x_k denote the independent variables. $\beta_0, \beta_1, \dots, \beta_k$ are the unknown parameters, and β_0 is the regression constant. From the results of correlation analysis, the interrelationships were calculated, and the significance of each multiple linear regression result was tested using $P < 0.01$ as the criterion, and the optimal model was selected based on the statistical characteristics (P, R^2) (Li et al. 2020).

Usually, computers are used to solve such problems and quickly discover the appropriate mathematical expression between variables, namely the regression equation, while ensuring the accuracy of the results and reflecting the practical value of the regression. In practice, most complex problems are nonlinear multiple regression (Gibbons and Chakraborti 2014). Linear regression has some important premises, such as independent variables and dependent variables must have a linear relationship, no appearance of any outliers, and no heteroscedasticity; samples should be independent and identically distributed; error items should mean 0; variance constant obeys normal distribution; and there is no multicollinearity and autocorrelation (Woli et al. 2004).

Stepwise regression is a variable selection method that is based on forward introduction and variable in and out. The core of the regression model is to remove the insignificant variables from the regression model and introduce new variables into the regression model. In recent years, some scholars have developed a Bayesian hierarchical linear regression model, which can more effectively reveal the impact of land use and land cover on watershed water quality (You and Yan, 2017).

Redundancy analysis

Another direction in correlation analysis is to perform Redundancy Analysis (RA). In 1936, Hotelling proposed typical correlation analysis, which extended linear correlation analysis to the correlation of two groups of variables (Hotelling 1992). The calculation principle of the redundancy calculation analysis is shown in Fig. 3, whereby it means that when dealing with the relationship between two groups of variables, typical correlation analysis is performed first to find two groups of typical variables, and then a linear regression model is established with one set of original variables as the response variables and another set of typical variables as the explanatory variables (van den Wollenberg 1977).

Redundancy analysis was used to determine the positive/negative relationships between landscape features and water quality parameters, as well as the cumulative explanatory power of significant landscape indicators at different riparian buffer widths (Choi and Seo 2021). Redundancy analysis is a ranking method in ecology to explain the relationship between species information and environmental variables, which can synthesize the influence produced by multiple variables and effectively evaluate the influence of one set of variables on another. When evaluating the directional correlation between many predictors and outcome variables, the regression model is often accompanied by dimension reduction techniques (Shen et al. 2015). After a series of transformations and screening, redundancy analysis method

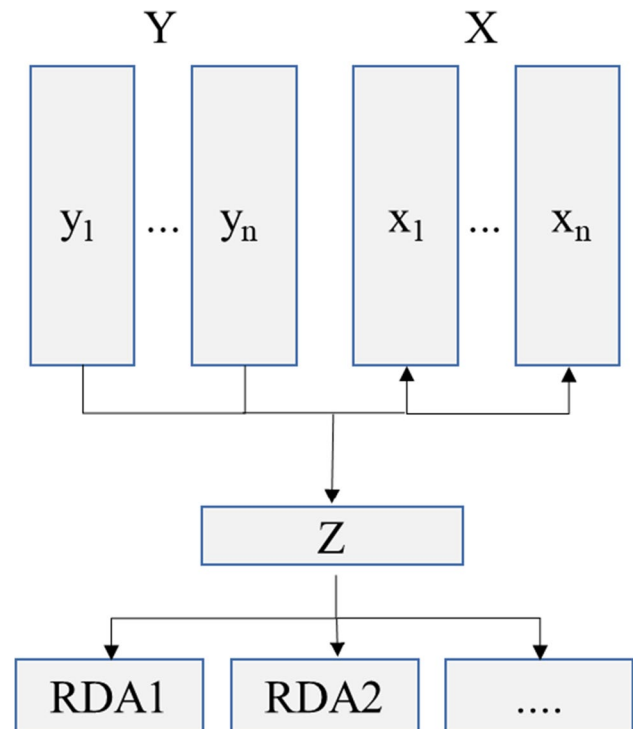


Fig. 3 Calculation principle of redundancy calculation analysis

can effectively simplify the number of variables to create conditions for researchers to further simplify the analysis (Tong and Chen 2002).

The biggest advantage of redundancy analysis is that it not only independently maintains the contribution rate of each variable to plant community change but also minimizes the number of environmental variables. Redundancy analysis directly takes the environmental variables of interest as constraints into consideration in ranking analysis, thus greatly reducing the scale of environmental variables, which is called ranking method under constraints. In addition, extended redundancy analysis (ERA) has been developed in recent years and is widely used in the study of component regression models. Choi and Seo (2021) proposed copula-based redundancy analysis (CRA) to improve the performance of regression-based ERA; the results show that CRA is significantly better than regression-based ERA.

Multivariate spatial regression analysis

At present, the effect of ecological landscape on individual water quality indicators can be estimated with multiple regression models (Ding et al. 2016). To quantitatively study the relationship between water quality changes and land use indicators, a multiple stepwise regression analysis model was therefore used to establish the response of water bodies to land use patterns and water quality relationships within

different buffer zones, and was used to identify the environmental or landscape variable factors that best explained the water quality indicators. The formula is shown in Eq. (7).

Spatial regression analysis refers to the regression analysis considering the relationship of the research object. Spatial regression analysis models can be divided into spatial lag model (SLM) and spatial error model (SEM) (Guo et al. 2016). Moreover, spatial regression analysis should first conduct spatial correlation test, and Lagrange multiplier is usually used for test; the model parameters are generally estimated by maximum likelihood estimation (Lee 2004).

The SLM and SEM model equation can be expressed as:

$$y = t_0 W_y + x\beta_0 + \varepsilon, \varepsilon \sim N(0, v^2) \quad (8)$$

$$y = x\beta_0 + u, u = \lambda W_u + \varepsilon, \varepsilon \sim N(0, v^2) \quad (9)$$

where y is the dependent variable, x is the independent variable, t_0 is the regression coefficient, β_0 is the parameter, u is the intercept, λ is the spatial autoregressive coefficient, W is the weight, and ε is the error term.

In practical problems, the classical least squares regression is the most widely used model, which well describes the process of conditional mean distribution of dependent variables affected by independent variables. The ordinary least squares linear regression model assumes the same linear relationship between the dependent and independent variables in all spatial units in the study area and uses the least squares method to estimate the unknown parameters of the multiple linear regression equation. The matrix expression of the linear regression model takes the form:

$$y = X\beta + \varepsilon \quad (10)$$

$$y = \begin{bmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{bmatrix}, X = \begin{bmatrix} 1 & x_{11} & \dots & x_{1p} \\ 1 & x_{21} & \dots & x_{2p} \\ \dots & \dots & \dots & \dots \\ 1 & x_{n1} & \dots & x_{np} \end{bmatrix}, \beta = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \dots \\ \beta_n \end{bmatrix}, \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \dots \\ \varepsilon_n \end{bmatrix} \quad (11)$$

where y is the dependent variable, X is the $n \times (p+1)$ order regression design matrix of the independent variables, β is the parameter vector, and ε is the random error vector. Equation (11) has 2 basic assumptions: the independent variables are linearly independent, X is a full-rank matrix, and the sample size n is larger than the number of independent variables p . The random error term ε satisfies a normal distribution and is independently isotropic.

In general, the least square method is often used to fit the independent variables and dependent variables in cross-sectional data; that is, the regression coefficient is independent of the geography of the sample data; the distribution of variables in space is random; and there is no obvious data aggregation characteristics like the upward graph. Partial

least squares regression is a predictive modeling method, which is related to PCA; it can overcome the shortcomings of classical regression analysis, thus achieving better simulation and analysis results (Xie and Chen 2022). Unlike classical forms of data, the spatial heterogeneity of regression relationships can exist in some cases where spatial data are correlated.

To overcome the inability of the least squares method to describe spatial auto-correlation and the unsteadiness of spatial data, GWR model takes into account the spatial heterogeneity of the data into the regression model and analyzes the local characteristics of the data. The GWR model can be viewed as an enhanced general linear regression model that embeds the geographic sites of the data into the regression parameters (Brunsdon et al. 1999; Wang et al. 2017). GWR based on multiple linear regression and geographic location information, which fully considers the non-stationarity of space and uses local rather than global parameter prediction and simulation (Tu and Xia 2008), can better consider the spatial dependence and heterogeneity of dependent variables and independent variables, and make the regression structure more reliable. In addition, the overall trend is robust under the change of spatial scale (non-bandwidth) and spatial granularity (Dong et al. 2018). Its formula is:

$$W_i Y = W_i X \beta_i + \varepsilon_i \quad (12)$$

where W_i is the $n \times n$ order diagonal matrix, which is a function of the distance from observation point i to the nearest neighboring observation point; Y is the $n \times 1$ order observation vector of the dependent variable collected at n points; X is the $n \times k$ order independent variable matrix; β_i is the $n \times 1$ order parameter vector corresponding to observation point i ; ε_i is the $n \times 1$ order error vector, which follows a normal distribution with constant variance.

In particular, GWR first expects the predictor variables to vary continuously in space in terms of their effects on the dependent variable. Thus, these relationships are assumed to be non-stationary, with the coefficients of each predictor variable varying from point i to the next point in a two-dimensional geographic space defined by grid coordinates (u, v) (or coordinates on a sphere), such that the regression equation takes the form:

$$\hat{y}_{(u_i, v_i)} = \beta_{0(u_i, v_i)} + \beta_{1(u_i, v_i)} x_1 + \beta_{2(u_i, v_i)} x_2 + \dots + \beta_{k(u_i, v_i)} x_k \quad (13)$$

Study of different spatial scales under remote sensing perspective

Scale is an important concept in geography. In real data, different regression processes can be performed at different spatial and temporal scales, such as global and local scales,

macro and micro scales, and short-term and long-term scales. The emergence of various phenomena is not only determined by one variable or one scale, and the analysis of land use in early studies was usually carried out based on a certain spatial scale.

In recent years, domestic and foreign scholars have started to analyze the relationship between river water quality and land use based on different spatial scales. Elsewhere, Rodrigues et al. (2018) analyzed the influence of land use on river water quality in the *Córrego Água Limpa* watershed, Brazil, based on the basin-wide scale. Shukla et al. (2018) analyzed the relationship between water quality and land use in the Ganga river basin, India, from two spatial scales: watershed and administrative area. Due to the differences in multi-scale patterns of land use, there is uncertainties in the study of river water quality in terms of land use patterns. The results (correlations) are affected by the size of the spatial analysis scale, but there are different conclusions on which scale of land use patterns can better explain the relationship (Fang et al. 2019). It is necessary to consider the analysis from different spatial scales. Ding et al. (2016) analyzed the relationship at different scales in the Dongjiang River basin and found that the watershed scale could better explain the effect of land use on river water quality than the buffer scale. However, Xu et al. (2020) studied at seven different spatial scales in the Huaihe River basin and found that a buffer zone with a radius of less than 20 km could better explain the effect of land use on changes in ammonia nitrogen and dissolved oxygen concentrations. It can be seen that when analyzing the relationship between river water quality and land use, there are differences in the appropriate spatial analysis scales for different watersheds. Therefore, it is necessary to compare different spatial scales in order to find a more significant analysis scale.

In addition, how exactly human activities on regional lands affect the quality of water bodies may vary at different spatial scales (Camara et al. 2019; Luo et al. 2018). When understanding the changes in water quality caused by land use practices, researchers use this method as it gives greater weight to land use (Kennen et al. 2008; Peterson et al. 2011). Watershed buffers such as riparian zones and hydrological sensitive areas (HSAs) are considered to be key influences on water quality in the region (Giri et al. 2018), whereby HSAs refer to regions with high runoff tendency in the basin (Faruque 2019; Qiu et al. 2014). HSAs mainly produce and transport pollutants to rivers and affect river hydrology, and although interesting, there are also shortcomings. Firstly, there is no unified method to determine the width of riparian zone. Secondly, given the hydrological connectivity of spatial changes in landscape, riparian zone is not an alternative indicator of hydrological sensitivity. Many multi-scale referred research focus on the following points, including comparison of buffers with the whole basin, comparison of

multi-scale basins, and comparison of buffer extents (Kolpin 1997; Shen et al. 2015).

Conclusions and discussion

Discussion

Remote sensing technology is of great value in monitoring and studying land use/cover change as well as testing remote sensing empirical models to help water quality monitoring, assessment, and drawing spatial distribution of water quality parameters using geographic information systems. With the continuous development of multi-source satellite remote sensing data (multi-band, multi-platform), fusion methods, and technologies, the spatial and temporal resolution and continuity of satellite remote sensing data are further improved, the image quality is improved, and the potential value of satellite remote sensing data is fully utilized and played. Because of the differences in satellite and sensor characteristics and the applicability of specific element inversion algorithms (such as the algorithm based on thermal infrared remote sensing information inversion of surface temperature is only applicable to sunny conditions), monitoring land use change and water cycle elements using only a single satellite platform is difficult to meet the requirements of resource management for spatial and temporal resolution, spatial and temporal continuity, and accuracy of monitoring elements (Kosolapova et al. 2021). At present, remote sensing monitoring is only one of the applications of remote sensing technology in surface water environmental monitoring, and the uncertainty is high. In the future, multi-period satellite remote sensing images can be acquired based on Google Earth Engine platform to accurately extract river–lake–reservoir and related land use information to conduct time series analysis to obtain water quality changes and serve as the scientific basis for taking corresponding measures (Wagner et al. 2019; Wagner and Fohrer 2019).

In the future, it is critical to combine PCA, typical correlation analysis, and multiple regression analysis, so that future studies can still carry out regression modeling when there are multiple correlations between the independent and dependent variables, or even when the number of samples is less than the number of variables. Regression modeling is performed even when the number of samples is less than the number of variables. Regression modeling can be used in the case of multiple correlations between independent variables and dependent variables, or even the value of samples is lower than the value of variables. If we want to effectively calculate and analyze the relationship between the influencing elements of Carrying Capacity of Water Resources (CCWR) and the index, we should require a large number of data on the influencing factors of CCWR, which is generally

difficult to achieve at this stage. Therefore, it is necessary to establish a water resources information collection system to collect data. In the future, it is necessary to obtain more information about various aspects affecting the CCWR to obtain a more comprehensive description of the index value of it. In the future, more methods such as machine learning and artificial neural network can be used to estimate the mechanisms of influence between water quality and land use (Zhang, 2014). In contrast to traditional methods of building regression equations, machine learning algorithms have been used to estimate water quality to predict concentrations of water quality indicators in different watersheds with different land use practices (Bhattarai et al. 2021). Surface water quality problems arise with the development of human society, and land use has an important impact on the change of water environment and water quality. Similarly, the change of water environment is inseparable from the development of population, economy, politics, and technology in the basin. In order to accurately and quantitatively discuss how land use and its changes affect surface water bodies, more comprehensive considerations are needed in the future to serve as a scientific basis for taking appropriate measures.

Conclusions

This paper summarizes the published studies and concludes that (1) land use change has a series of profound effects on ecological process, surface runoff, and hydrological cycle. It then affects the safety of river water quality. Discussing the mechanisms of influence between water quality and land use is of great significance to land use management planning and effective protection of water ecological environment resources. (2) Different spatial resolution remote sensing data sources have their own advantages and limitations. Based on the statistical results of literature, the medium-spatial-resolution remote sensing data sources are widely used in the study of the relationship between land use and water quality. (3) Correlation analysis, regression analysis, and redundancy analysis in multivariate statistical methods have been widely used in exploring the relationship between land use and water quality. Studying the relationship between land use and water quality variables can reduce the cost of river water quality monitoring. The estimation of these relationships can provide a prediction basis for river water quality and reduce the need for periodic sampling process of most rivers.

It is difficult to accurately understand the mechanisms of influence between water quality and land use because it relies on many influencing factors. The study on the influence mechanism of land use on water quality indicators has become a hot topic of scholars in China and abroad. The research on the relationship between the two by using remote sensing data and GIS has gradually increased. The

periodicity and quantification of remote sensing technology can be used to solve some over-generalization problems and provide modern technical support for dynamic monitoring. In the future, more in-depth dynamic monitoring combined with remote sensing images is needed to overcome the overrun phenomenon in the traditional monitoring data acquisition and processing.

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Declarations

Ethical approval Not applicable.

Consent to participate Not applicable.

Consent for publish Not applicable.

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