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REVIEW

"Source–sink" landscape pattern analysis of nonpoint source pollution using remote sensing techniques

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Abstract
Research on the "source–sink" landscape pattern of nonpoint source pollution is of great significance to natural resource management, environmental protection, water quality improvement, nonpoint source pollution prevention and control, and ecological security pattern construction. Remote sensing has proven by many scholars as a practical and effective technique to study landscape patterns and nonpoint source pollution. However, there are still many obstacles to the application of remote sensing technology, such as classification errors, scale effects and the issue, whereby landscape metrics cannot describe the landscape information comprehensively. In view of the characteristics of the macroscale and multi-scale of remote sensing, the analysis of landscape patterns is the basis for the study of the relationship research between patterns and ecological processes, and it is also the key to the study of landscape dynamics and functions. This paper attempts to summarize the representative results and the challenges of remote sensing in the study of the source and sink landscape of the nonpoint source pollution landscape and provide corresponding solutions as a reference for future research.

Keywords Land use classification · Multi-satellite · Watersheds · Ecological process · Water quality

Introduction

Compared with the characteristics of point source pollution, nonpoint source pollution is widespread and difficult to quantify (Liu et al. 2017). With the intensification of urbanization, nonpoint source pollution has gradually become the major source of water pollution (Qiu et al. 2008). In total, 40% of the world's agricultural production accounts for 85% of the world's total annual water consumption, and by 2050, there will be 1 billion hm2 of natural ecosystems converted into agricultural use (Banerjee et al. 2016). Agriculture has become the main source of nitrogen and phosphorus pollution (Eisavi et al. 2017). Under the premise that it is difficult to achieve pollution reduction through the control of agricultural development and inhibition of nonpoint source pollution, the relationship between landscape patterns and sources of nonpoint source pollution and the optimization of landscape patterns to improve nonpoint source pollution have become the primary aspects of this research (Diebel et al. 2009).

Due to the rich type of watershed landscapes, it is necessary for nonpoint source pollutants to pass through different landscapes as they travel from the place of origin to the water flow. Some landscapes in the basin play a role of "source" as the output of pollutants, some act as "sink" for reducing the nonpoint source pollutants, while others function as transmitting channels. Therefore, according to the different effects of nonpoint source pollution formation and reduction, different landscape types can be divided into two kinds of landscape—"source" and "sink." As the "source" landscape contributes much to the output of pollutants, while the "sink" landscape is more capable of reducing nonpoint source pollution, the characteristics, combinations and spatial distribution of different landscapes will all have significant impact on nonpoint source pollution. Under the socioeconomic development condition that the discharge of agricultural pollutants is difficult to reduce because of the pressure of

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intensive agricultural development, studying the relationship between "source–sink" landscape pattern and nonpoint source pollution can provide technical support for optimizing the landscape pattern and controlling nonpoint source pollution in watershed. From the perspective of nonpoint source pollution transmission, the composition of "source–sink" landscapes encountered by nonpoint source pollutants (N, P, etc.) in the transmission process will directly affect their contribution to water pollution. At the landscape scale, different landscape types and spatial combinations of sources and sinks have an important impact on the transmission of nonpoint source pollution. Therefore, the extraction of source and sink pattern information in the basin landscape is the basis for the study of nonpoint source pollution.

The advantages of remote sensing technology, such as multi-phase, multi-resolution and large-scale synchronous observations, have made it the main data source for landscape pattern research (Luft et al. 2016). The development of remote sensing technology has led to an increasing number of satellite and airborne platforms that cover a wide range of spatial and temporal scales and can detect landscape changes at different scales (Jorgenson and Grosse 2016). Compared with the use of a single data source, through the integrated use of multi-sensor remote sensing data, researchers can extract landscape pattern information more accurately (Betbeder et al. 2015). On the one hand, with the aid of such remote sensing technology, researchers can easily obtain satellite images covering the entire experimentation area, which greatly facilitates the extraction of information from the landscape pattern and landscape scale; on the other hand, the history of remote sensing image data provides powerful data support for studying the dynamic evolution of landscape source and sink patterns. On the basis of reflecting the information of source and sink landscape patterns, remote sensing technology is used to extract the specific ecological process, revealing the role that the landscape pattern played in the specific ecological process. Jha et al. (2007) indicate that remote sensing will have a great potential in six aspects, such as exploration and assessment of groundwater resources, groundwater pollution (Vetrimurugan et al. 2017), hazard assessment and protection planning, hydrogeological data analysis and process monitoring.

The paper will discuss the achievements, problems and future development of remote sensing in the study of the source and sink landscapes of the nonpoint source pollution landscape from the following three aspects: (1) "source–sink" landscape pattern information extraction of nonpoint source pollution in a watershed; (2) the application of remote sensing technology to nonpoint source pollution; and (3) study of the relationship between landscape patterns and nonpoint source pollution.

"Source–sink" landscape pattern information extraction of nonpoint source pollution in the watershed

Landscape feature extraction based on remote sensing data

The "source–sink" landscape pattern information in a basin is the basic data of landscape research. With the development of remote sensing technology, using satellite images to obtain landscape pattern data has become the primary data collection method in the study of landscape pattern.

Landscape pattern information extraction from multi-satellite

In the course of the development of remote sensing technology, different types of sensors have been produced for different design purposes. Sensors differ in spatial resolution, temporal resolution, spectral resolution and radiation resolution. In the process of literature investigation, according to the different remote sensing sensors selected, the extraction of source and sink features is based on multispectral images, hyperspectral images and high-resolution images.

The band range of a multispectral sensor includes near ultraviolet, visible and thermal infrared, and the data for each band are easy to register. Landsat is the most representative satellite in multispectral remote sensing. Landsat is a series of terrestrial satellites launched by NASA in the USA (Hansen and Loveland 2012). The satellite imaging quality is high, and the band combination can basically meet numerous research requirements. The resolution of 30 m (15 m in the panchromatic band) can meet the requirements for the extraction of source and sink information in most cases. Using Landsat data, Senf et al. (2015) succeeded in capturing the spatial heterogeneity of the phenological dynamics and source–sink types in the study area and accurately extracted the land cover information in complex landscape conditions. Herrera et al. (2009) used Landsat data to compare the landscape differences between two different time stages and analyzed the change of landscape pattern by landscape metrics. Considering the scale effect in landscape studies, Parent and Volin (2016) compared land use data with 1- and 30-m resolutions (based on Landsat data) and found that most metrics of landscape scale have strong correlations, while patch-level metrics are weakly related or even irrelevant. After fully excavating the characteristics of the spatiotemporal scale of remote sensing data, Zhang et al. (2014) proposed a new method of landscape analysis in the basin, which significantly improved the extraction precision of impervious surface and provided reference for the research and ecological management of nonpoint source pollution in the basin.

Compared with multispectral sensors, hyperspectral sensors with hundreds or even thousands of bands can, through different combinations of bands, effectively reflect the different surface objects spectral reflection characteristics of the difference to achieve accurate distinction between heterogeneous objects. Yokoya et al. (2014) presented a method of fusing airborne hyperspectral and mapping light detection and ranging (LiDAR) data for landscape visual quality assessment, and the research results contribute to landscape assessment and optimization of landscape spatial patterns. High time resolution satellites can obtain continuous monitoring data with "day" or even "hour" as a result of the short revisit period, which is of great significance to research of the dramatic evolution of landscape patterns (such as geological disasters and meteorological disasters).

In the development process of remote sensing technology, researchers have been in the pursuit of high spatial resolution of remote sensing images, from 1000 meters to 10 meters or even to decimeters, and sensors' spatial resolution has been significantly improved. A remote sensing image with high spatial resolution provides more detailed landscape information, and landscape pattern research based on high-resolution images has also made great progress. Based on high-resolution remote sensing images, Mui et al. (2015) applied the multi-scale geographic object-based image analysis (GEOBIA) method to distinguish wetland landscape types under different disturbance levels; although the results show that the overall high degree of landscape heterogeneity may be a negative for image segmentation and classification, the overall classification accuracy of wetland landscapes is still higher than 80%. Mairota et al. (2015) used very high resolution (VHR) remote sensing images in the large space to obtain the intra-granularity heterogeneity data of the landscape pattern, and the effects of the habitat surrounding the patches and the landscape structure on the habitat environment were studied by a linear mixed-effect model. Using high- and medium-resolution images, Tormos et al. (2011) calculated landscape classification data by comparing the spatial metrics based on two different classification data sets, and he proved that, compared to the medium-resolution data, the spatial metrics calculated based on the high-resolution image data can more finely characterize the landscape spatial structure information near the river and reliably quantify the main attribute information of the riverbank vegetation. In view of the problem of remote sensing information extraction and the scale dependence of impervious surface, Zhang et al. (2015) tried to solve it from two scales, pixel and sub-pixel, and the results effectively improve the extraction precision of the impervious surface.

Problems in current research

In the process of selecting remote sensing data, a single data source often exhibits the phenomenon of missing data or poor-quality data in some area (such as cloud cover). The solution to this problem is often to use multi-source data instead of a single data source. For example, Herrera et al. (2009) made use of MODIS data to make up for missing Landsat data, which ensures the integrity of the research data. The data generated by the different sensors have different characteristics. When the spatial resolution of the sensor is high, the spectral resolution is often low, and vice versa. However, in the course of research, we hope to obtain high-spatial- and high-spectral-resolution image data, and thus, the image fusion method has arisen at a historic moment. Image fusion means that, through image processing and computer technology, a multi-source channel is collected on the same target image data; then, the best information in each channel is extracted, and finally, the high-quality image is synthesized. This method can improve the utilization of image information, improve the accuracy and reliability of computer interpretation, and improve the spatial resolution and spectral resolution of the original image (Ozdogan et al. 2010).

The extraction of landscape-type information is an important application of remote sensing (Rezapour and Moazzeni 2016), but in the process of handling the remote sensing data to obtain the classification data, the image error or classification error will cause uncertainty of the results, and this uncertainty is inevitable. One possible reason is the mis-representation of ground objects in remote sensing data grids. Under the condition of different grid sizes, i.e., different resolutions, the landscape information reflected by the remote sensing image is same, although the real landmarks should be different. Alternately, landscape information cannot be objectively represented majorly due to the classification process as the classification accuracy of any classification method is relatively low and cannot adequately reach the level of an absolute true reflection of the landscape information.

The future research direction

This article posits that the future research of landscape "source–sink" information extraction should start from two aspects to reduce the uncertainty of the remote sensing data and improve the accuracy and credibility of the classification results. First, in the choice of data source, on the basis of multispectral and high-resolution sensor data, synthetic aperture radar interferometry (InSAR) should also be chosen as another data source (Lu et al. 2015). Compared with traditional optical remote sensing images, InSAR data can provide texture information and height information, that is, on the basis of the "spectrum" feature, the feature of the texture is increased, which provides a more detailed description of the characteristics of a particular landscape type. In view of the spectral characteristics difference between different water bodies, Zhang et al. (2013a, b) explored a new approach to water adaptive extraction based on local end member spectral characterization. The result shows that this method can extract all types of water information precisely and is not affected by different spectral features. And he also proposed a new method of texture feature extraction, which is based on the direction measure and a gray-level co-occurrence matrix (GLCM) fusion algorithm, and the experimental results demonstrated that texture feature extraction based on the fusion algorithm achieved a better image recognition, and the accuracy of classification based on this method has been significantly improved (Zhang et al. 2017a, b, c). Followed by the choice of classification methods, this paper is concerned that the existing remote sensing data can meet the data needs of classification at this stage, but the classification results are unsatisfactory because the classification method is lagging behind the data development, so the development of a classification method will effectively promote the development of landscape research. The characteristics of landscape spatial heterogeneity determine the complexity of the landscape source types, and there are many influencing factors, and a single feature cannot distinguish these types. Only when a fusion map and spectral feature classification method is established can scholars distinguish the "source–sink" landscape accurately and reliably (Immitzer et al. 2012).

Landscape pattern information extraction based on landscape metrics

Landscape metrics have been applied to analyze species composition and spatial configuration based on plaque mosaic data (such as vegetation type, land use type or soil type), which can quantitatively reflect the landscape pattern information. The landscape metrics can be used to describe the spatial composition and the spatial configuration of the landscape, with which the landscape composition represents the plaque species and its degree in the landscape and the spatial configuration of the landscape represents the spatial characteristics and arrangement, location and orientation of the patch, patch type or landscape level. Remote sensing and GIS technology provides a data basis for quantitative calculation of landscape pattern metrics. The calculation of the landscape metrics is usually divided into three levels: patch level, type level and landscape level. According to the different landscape features described by the metrics, the landscape metrics can be divided into area/density/edge metrics, shape metrics, core area metrics, contrast metrics, isolation/proximity metrics, aggregation/separation metrics, connectivity metrics and diversity metrics (Lausch and Herzog 2002). In the extraction of landscape information, the landscape metrics should also be considered in terms of relevance under the premise of the study to be selected. According to the different research areas, the scholars chose different landscape metrics and used different analysis methods to extract the landscape pattern information. For example, Xiao et al. (2016) selected five landscape pattern metrics: patch density, edge density, shape metrics, diversity metrics, aggregation metrics and three man-made activity indicators (human activity intensity, distance from town and road) to analyze the relationship between soil landscape pattern dynamics in the study area and human activity, which shows that the soil landscape becomes more fragmented during the research period.

Su et al. (2014) integrated remote sensing, a geographic information system, landscape metrics analysis and a spatial regression method to quantify the changes of agricultural landscape patterns in response to urbanization at a regional scale. By selecting four indicators of gross domestic product (GDP), the total population (TP), the proportion of non-agricultural population (NAPP), and the expanded intensity metrics (EII), the research effectively reflected the process of urbanization, and EII is the most effective indicator to explain the change of agricultural landscape pattern at the regional scale. Using redundant analysis, Shi et al. (2016) analyzed the relationship between land use patterns and water quality. The results show that there is a strong correlation between a landscape pattern and water quality, and the landscape near a river bank is more influential than the overall landscape. Further analysis of the spatial development model shows that the size, density, aggregation and diversity of the landscape pattern are important factors affecting water quality. In addition, the paper also notes that the landscape metrics have a scale effect when reflecting the landscape pattern information. Fan and Myint (2014) mentioned that the use of remote sensing land cover classification and landscape metrics has contributed to scholars' understanding of landscape structure information, but an error in land use classification may lead to more serious errors in subsequent landscape analysis. Compared to landscape metrics, spatial autocorrelation metrics are directly based on remote sensing images to calculate the degree of landscape fragmentation. By comparing the results of two sets of landscape metrics and the spatial autocorrelation coefficient, the results show that there is a strong correlation between landscape pattern metrics and the spatial autocorrelation coefficient.

A watershed landscape can produce different classification results under different classification schemes because the landscape pattern metrics are calculated on the basis of the image classification data, and therefore, they will be different under different classification results. For a specific research area, which classification scheme is the most suitable for calculating landscape metrics to reflect pattern information is a worthwhile discussion. Schulz et al. (2017) using landscape metrics analyzed the relationship between land cover and landscape diversity changes; based on MODIS land use products, he calculated five landscape metrics and analyzed the relationship between the pattern and the process at different spatial levels. Jaafari et al. (2016) integrated the application of remote sensing image interpretation and a landscape ecology method to analyze the dynamic changes of landscape in the study area, among which the landscape is divided into orchards, healthy grassland, degraded grassland, greening and water. Through the calculation of landscape metrics, he obtained information of landscape transformation and fragmentation and analyzed the driving force of "source–sink" landscape patterns.

Classification error cannot be avoided when a remote sensing image is used to extract the "source–sink" landscape information of the river basin (Knudby et al. 2014). How does the classification error affect the landscape pattern analysis results in the process of using the classified data to calculate the landscape pattern metrics? To solve this problem, Shao and Wu (2008) discussed the influence of classification error on landscape metrics and put forward analysis to improve the reliability of landscape pattern research. Reyes et al. (2016) studied the effects of different classification schemes on the measurement of landscape heterogeneity. The results show that, compared with the K-nearest neighbor method, the SVM classification results can better reflect the heterogeneous information. In view of the fact that there are many random forest and SVM methods in the relevant articles (Attarchi and Gloaguen 2014; Rodriguez-Galiano and Chica-Rivas 2012), it is reasonable to believe that, in the present research, the random forest method is more suitable for extracting landscape information than other classification methods (Cracknell and Reading 2014).

Along with the continuous development of watershed landscape pattern research, the study of landscape metrics has also made remarkable progresses. There are two reasons for the development, one of which is the improvement of remote sensing technology, which increases the precision of data sources, and the other is that more and more new metrics have been created for this specific purpose. However, scholars should not neglect that there are still problems in the research of landscape pattern metrics. The first is the scale problem, which is also the problem that must be paid attention to in the study of landscape patterns. In the process of calculating the landscape pattern metrics by using the remote sensing image data as the input data, the grid size of the remote sensing raster image, which is the spatial resolution, will have an impact on the calculation results of the landscape metrics. If the image pixels are too large, the details may be ignored. In contrast, if the grid is too small, there exists redundant information, and the amount of data will be too large. Therefore, for a specific study area, it is necessary to select a suitable resolution of remote sensing images as a basic data. Second, the ecological problems of landscape pattern metrics should also be considered. The instantaneous imaging of the sensor determines that the image can only reflect the pattern information at the imaging time, but the pattern and process interact with each other, which means that the process forms the pattern, while the pattern reflects the process. In the reference literature, the vast majority of landscape pattern metric calculations focus on the situation of the landscape, but there are few studies dealing with the process that affects and produces the landscape.

Obviously, compared with the pattern at a particular moment, scholars are more concerned with the ecological process behind the pattern; therefore, it is not adequate to only use the metrics to study the pattern information.

This article notes that future landscape pattern metrics research should pay attention to the solution of the problems mentioned above. From the point of view of multi-scale problem, reasonable-resolution image data should be selected according to the scope of the study area. The existing remote sensing techniques are capable of imaging from decimeter to km, and through the method of sample selection, researchers should compare the advantages and disadvantages of the calculation results of the landscape metrics in different resolution images and then select the most suitable one as the raw data source for the specific experimentation area. From the point of view of the ecological problem, the study of landscape metrics should be combined with specific ecological processes. A comprehensive study of landscape metrics and watershed non-point source pollution is a successful example (Jiang et al. 2013). It is a time–space continuous process by which non-point source pollutants accumulate in the basin. The new metrics proposed by the author combine the generation and transmission of nonpoint source pollutants, and the calculation results effectively reflect the structural information of "source–sink" landscape patterns.

According to the references, the use of remote sensing technology to extract "source–sink" information has been the mainstream method for landscape pattern research. The characteristics of large-scale simultaneous monitoring of remote sensing make the study of landscape patterns easier to implement. The development of remote sensing technology, especially the launch of high-resolution satellites, provides an opportunity to improve the accuracy of landscape pattern research.

Application of remote sensing technology in nonpoint source pollution calculation

Nonpoint source pollution refers to the pollution caused by dissolved or solid pollutants injected into the receiving water and, in the case of a large area of precipitation, leaching and erosion of runoff (Duan et al. 2009), which usually includes agricultural nonpoint source pollution (Kleinman et al. 2015), soil and water loss nonpoint source pollution (Zhang et al. 2013a, b), urban nonpoint source pollution (Mitchell 2005) and rural life nonpoint source pollution (Ongley et al. 2010). Nonpoint source pollution is characterized by the random occurrence of time and the form of intermittence, resulting in that conventional environmental monitoring technology is difficult to achieve a comprehensive monitoring; When the model is used to simulate the nonpoint source pollution, it is difficult to fully reflect the actual situation by inputting the measured input parameters, which affects the simulation effect of the model (Bai et al. 2016). The traditional nonpoint source pollution monitoring and analysis method is field investigation and sampling analysis, which is subject to human, material, climate and hydrological conditions. Since the mid-1980s, the development of satellite remote sensing technology has provided a new approach for nonpoint source pollution research in watershed water environments (Singh et al. 2016). Remote sensing is a process of estimating the surface parameters by measuring the electromagnetic radiation from the land surface. It makes up for the defects of traditional nonpoint source pollution analysis and quantitative calculation and plays an important role in water environment and pollution analysis with the advantages of real time, efficient, durable, large amount of data and wide observation (Schmugge et al. 2002).

Inversion of water pollutants by remote sensing technology

Nonpoint source pollution contains numerous types of pollutants (de Oliveira et al. 2017). As many as 40 types of pollutants have been detected in conventional testing, and through remote sensing technology, many components can be monitored. The water quality is based on the correlation between the components (SPM, SD, TN, COD, etc.) and chlorophyll content of the water body, and this correlation provides an indirect means for quantitative acquisition of nonpoint source pollutants by remote sensing. There are many remote sensing data sources, and different types of data sources have different applications in the calculation of nonpoint source pollutants.

Widely used remote sensing data include US Landsat satellite data, French SPOT satellite data, meteorological satellite NOAA data, Indian remote sensing IRS system data and Japan JERS satellite-received multispectral image data. Landsat data are the most widely used data currently. Since the launch, MSS data have been applied in nonpoint source pollution studies. Bands 1–7 of TM5 can be used for water recognition, while bands 1–4 (the visible-to-near-infrared band) reflect the most information (Kovalskyy and Roy 2013). Compared to Landsat, the biggest advantage of SPOT is its 10-m space resolution; each band exhibits a saturated reflection at high turbidity (Durand et al. 2014), while SPOT1 and SPOT2 were saturated at 500 mg/L, so

Table 1 Brief comments of sensors

Satellite	Sensors	State	Band number	Revisit period (day)	Resolution (m)
Landsat	MSS	US	4	18	79
	TM		7	16	30
	ETM+		8	16	30
	OLI/TIRS		9	16	30
SPOT-6	HRV	FRA	5	0.5	10
IRS-P6	AWIFS	IND	4	5	56
	LISS-3		4	24	23.5
	LISS-4		3	5	5.8
JERS-1	OPS	JPN	4	44	18
TERRA AQUA	MODIS	US	36	0.25	250/500/1000

it is not applicable when the water is highly turbid. Moderate-Resolution Imaging Spectroradiometer (MODIS) has 36 bands (Duan et al. 2014), and the data in bands 1, 2, 8, 9 and 13, 14, 15, 16 can be used to quantify the calculation of turbidity, TMS, chlorophyll and pollutant content (Heumann et al. 2007). Advanced Very High Resolution Radiometer (AVHRR) is a sensor mounted on a series of satellites so that it can provide day-to-day visible images and thermal infrared images. In a study based on AVHRR data, the chlorophyll content of cyanobacteria increased the reflectivity of the near-infrared band of water, so the relationship model with nonpoint source pollution parameters (SS, SD, COD, BOD, TN, TP, DO, etc.) could be established. Hyperspectral remote sensing can be separated into hundreds of narrow bands to receive information in all spectral ranges of the visible band, near-infrared band, mid-infrared band and thermal infrared band. Compared with Landsat and SPOT, hyperspectral sensors can detect many features of terrestrial that satellites cannot and identify various features with special spectral characteristics, especially in water, such as insoluble organic matter and chlorophyll A (Wingle et al. 1999). The application of hyperspectral remote sensing technology means that the improvement of nonpoint source pollution monitoring technology and monitoring content will greatly improve the accuracy and reliability of the prediction results of the nonpoint source pollution model in the watershed (van der Meer et al. 2012). Some brief comments of sensors used in the previous studies can be seen in Table 1.

The advantage of remote sensing in monitoring nonpoint source pollution

As an important means of data acquisition and dynamic monitoring of nonpoint source pollution, remote sensing technology can clearly reflect the pollution status and spatial distribution characteristics of the region or the entire basin (Tang et al. 2009), and it is characterized as having a high viewpoint, wide vision, multi-angle view, rapid data acquisition, low cost, reliable information, etc. When applied to watershed nonpoint source pollution research, remote sensing has many advantages as follows. First, through satellite or aircraft used for high-altitude observation of the earth, scholars can carry out large-scale synchronous monitoring and get environmental information data frequently, which is characterized as fast, accurate, comprehensive and comparable. Using remote sensing technology, scholars can detect water pollution, air pollution and soil pollution over time (Zare et al. 2017). Second, when using remote sensing technology to obtain nonpoint source pollution information, the information gathered has the advantages of wide range, easy access, large quantity, fast acquisition, short cycle and fewer limitations. Third, compared with the traditional method, the cost and the obtained benefits of remote sensing greatly save manpower, material resources, financial resources and time. In addition, with the support of remote sensing technology, scholars can directly monitor nonpoint source pollution in the watershed, and the processing of monitoring data can be directly applied to establish a quantitative model of nonpoint source pollution. Under the premise of multi-source remote sensing data, scholars can easily obtain the spatial distribution of the influence factors by way of remote sensing image processing, visual interpretation and computer interpretation. After determining the main nonpoint source pollution factor in the watershed, through the quantitative analysis of the nonpoint source pollution quantitative model simulation results, scholars can also grasp the reliability of prediction results macroscopically.

Quantitative extraction and simulation of nonpoint source pollution by remote sensing technology

The application of remote sensing technology has broad prospects in nonpoint source pollution surveying. While most research studies on nonpoint source pollution remained at the qualitative level in the early stages, at this stage, the application of remote sensing technology for nonpoint pollution places more emphasis on the description of spatial information and spatial characteristics of environmental processes, spatial information collection, estimation and simulation of nonpoint source pollution in watersheds through the use of watershed hydrological models.

Quantitative extraction of nonpoint source pollution information

Remote sensing technique is used to quantitatively extract nonpoint source pollution information. Most of the current research uses the method of regression analysis to establish the empirical formula between the remote sensing data band and nonpoint source pollution concentration and then quantitatively extracts the nonpoint source pollution information. Based on Landsat-8 remote sensing images, Chen et al. (2017) evaluated the colored dissolved organic matter in inland waters. Based on the spectral reflectance, remote sensing reflectance and irradiance, he proposed an empirical band ratio algorithm, and then by using a sorting method to determine the optimal band ratio, he finally obtained the information of dissolved organic matter in water. Using the imaging spectrometer to monitor point source and nonpoint source pollution in inland and estuarine waters, Fichot et al. (2016) described several pollution indicators and provided data assessment regarding the impact that wetland restoration and climate changes have on water quality. Through the onboard portable remote imaging spectrometer, the authors analyzed the turbidity, dissolved organic carbon and concentration of chlorophyll A in the estuary and compared the relationship between different pollutants by water samples. Ogashawara and Moreno-Madrinan (2014) developed a bio-optical algorithm that monitors the daily chlorophyll A concentration with a Medium-Resolution Imaging Spectrometer. The algorithm is applied to the data of four different periods, and the change of water environment in the study area is compared and analyzed. Although the above methods are simple, they also have a great dependence on the synchronization of nonpoint source pollution data and remote sensing data, and the accuracy of the method is susceptible. The best means to solve this problem is to establish a physical model between the reflection spectrum and the contaminant concentration, which has undergone a number of related basic studies. Through evaluation of the ecological status and water environment potential of large lake water bodies by remote sensing, Sandstrom et al. (2016) used the MERIS data to invert the chlorophyll A, total suspended matter and colored dissolved organic matter in the Swedish lakes. By establishing three potential candidate indicators to assess the extent of lake pollution, the authors explained the changes in the composition of fish and assessed the fish status. Rostom et al. (2016) used low spectral remote sensing to evaluate the nonpoint source pollution of lakes. By inputting the spectral data collected by the portable FieldSpec_3 ASD spectral radiometer into the water pollution prediction model, the authors obtained the concentration information of the lake nonpoint source pollutants and then analyzed the correlation between chlorophyll A concentration, heavy metal concentration and spectral reflectance. Based on the hyperion data of the EO-1 satellite, Kar et al. (2016) classified the nonpoint pollution sources and studied the spatial variability of nonpoint source pollutants in watersheds. Through analyzing the spectral data, collected by spectrograph, spectral radiometer and FieldSpec_4, the authors put it into the spectral database for the spectral absorption depth analysis, and then according to the spectral depth of the corresponding absorption characteristics, the authors can use the multiple regression method to evaluate the concentration of the same metal ions and thus achieve remote monitoring of nonpoint source pollution.

The problem of nonpoint source pollution includes many contents. At the present stage, there is still uncertainty about the accuracy of remote sensing monitoring and inversion, and the inversion metrics cannot completely replace the conventional pollution metrics. Therefore, the application of remote sensing is not a comprehensive reflection of the nonpoint source pollution in the usual sense. At this stage, it is mainly aimed at a few pollution projects. For the selected watershed pollution project, first researchers have to distinguish clear water boundary conditions. Second, according to the spectral characteristics of remote sensing pollutants, the necessary processing of remote sensing images is carried out to enhance the image recognition. In addition, the data obtained from the remote sensing image reflect the comprehensive information of the surface radiation across the water surface. However, factors such as water surface float, water depth and aquatic organisms contained in the water body affect the monitoring accuracy, making the monitoring data unable to fully reflect the structural condition of the water body. In the process of analysis, these interference factors should be dealt with one by one, and the researchers should eliminate interference information that is not related to the subject.

Simulation and prediction of nonpoint source pollution

In a watershed, the generation and movement of runoff is a very complicated process that is closely related to the hydrological parameters, such as land use, soil properties and hydrological conditions and precipitation, and the runoff movement involves multiple space attributes, such as the terrain and river. Therefore, the nonpoint source pollution model in the water basin environment requires a lot of spatial parameter information in the application, and the simulation of the model cannot be separated from the expression of the spatial characteristic parameters (Xue and Xia 2007). Appropriately, the advantage of remote sensing technology is the generation, organization and management of spatial data, which determines that remote sensing techniques can assist models in gathering, managing, analyzing, simulating and displaying spatially related nonpoint source pollution information. The main applications of remote sensing technology in nonpoint source pollution research include estimating soil erosion rate and soil erosion, simulating soil erosion's impact on the environment, and simulating surface runoff and water quality responses to LUCC changes. Another important aspect of remote sensing applications is the combination of the nonpoint source pollution model and establishing a prediction evaluation information system to identify high-risk areas and evaluate the effectiveness of governance measures.

Wang et al. (2012) established a "binary structure" based on spatial pixel modeling. The model uses remote sensing data to obtain the spatial and temporal processes of land use and its effect on nonpoint source pollution. Based on the spatial pixel, this model improves the estimation of nonpoint source pollution load on the basin scale. Based on the landscape contrast metrics, Shiels (2010) applied GIS and remote sensing technology to calculate the landscape metrics. The authors set up the grid landscape contrast metrics to reflect the contribution rate of the landscape to the nonpoint source pollution at a certain scale and analyzed the correlation between the landscape metrics and the nonpoint source pollution data obtained by monitoring. The results show that the agriculture-oriented landscape type plays a major role in the nonpoint source pollution. What is more, using the location-weighted landscape contrast index, Zhang et al. (2017a, b, c) quantitatively evaluate the influences of landscape composition and spatial structure on the transmission process of nonpoint source pollutants in different regions. Based on a high-resolution remote sensing image, Yan et al. (2005) obtained the data of landscape pattern in the watershed and then analyzed the relationship between the distribution of nonpoint source pollution and geological topography and hydrological conditions. Generally, in the process of building a quantitative model of nonpoint source pollution, based on remote sensing technology, the more types of nonpoint source pollution and the finer the classification, the more difficult it is to interpret the accuracy of interpretation. Ensuring the quality of the data source is important for the reliability of nonpoint source pollution quantitative models, such as the phase, resolution, clarity of remote sensing data, choice of software and level of references' details. At present, the range of electromagnetic waves researchers use is still limited, and there are many spectrums that remain to be further developed in future research of nonpoint source pollution. In view of the fact that the existing band combination method cannot accurately reflect nonpoint source pollution types and influencing factors, the ground survey and verification are still indispensable.

The research on the relationship between landscape pattern and nonpoint source pollution

The landscape pattern has an important influence on the water environment. In recent years, scholars have carried out a lot of research on the relationship between landscape pattern and water quality, and they have mainly discussed the response of various water environmental indicators (water chemical ions, conventional pollutants, nutrients, heavy metals, organic matter, aquatic organisms, etc.) of landscape patterns and the scale effect of watershed landscape patterns on the water environment (Ouyang et al. 2010). Quantitative analysis of the relationship between landscape pattern and water environment is mainly dependent on two types of methods. One is using multivariate statistical analysis techniques, including traditional correlation analysis, variance analysis, stepwise regression analysis and gradient analysis methods introduced by the field of community ecology research, such as corresponding analysis, canonical correspondence analysis and redundancy analysis. Through the above methods, parameters such as landscape pattern variables, watershed hydrological and geomorphological parameters and precipitation conditions were included in nonpoint source pollution models, such as SWAT (Sommerlot et al. 2013), and then from the process of nonpoint source pollution generation and migration distribution, the relationship between regional landscape pattern and water quality is demonstrated. The second is to simulate the response of water environment quality to the landscape pattern change with the aid of environmental mathematical models. By exploring the relationship between different landscape patterns and multi-year precipitation runoff, the researchers analyzed the water quality change characteristics in combination with a water quality simulation model, based on the quantitative assessment of landscape pattern change influence on watershed environment. In addition, the scale effect is an important content in landscape ecology research. On different spatial scales, especially in the riverbank scale and river basin scale, the difference of relationship between landscape pattern and water quality among different watersheds should always be concerned.

Research on the relationship between landscape metrics and water quality

From the perspective of nonpoint source pollutant transmission, the landscape pattern of the watershed plays an important role in the process of pollutant transmission. The process of a pollutant from the place of origin to the water body is under the comprehensive action of the landscape pattern and various geographic factors. The spatial combination of different "source and sink" landscape types will affect the efficiency of nonpoint source pollutants entering the water body. Comparison with the water quality can be effectively reflected by the water quality indicators, the landscape pattern represents the spatial distribution and combination of "source–sink" landscape types, and it is difficult to quantitatively evaluate because of the time–space complexity of the landscape pattern in the watershed. Landscape metrics can quantitatively reflect the "source–sink" landscape pattern information, and finding the relationship between landscape metrics and water quality indicators is an important aspect of the study.

Varanka et al. (2016) used the Spearman rank correlation test method to select the weak geometric parameters and used the new multivariate analysis method to study the relationship between water quality and surface landscape at basin scale. Ouyang et al. (2014) analyzed the interaction between land cover, landscape pattern and NPS pollution at the same time and used the temporal and spatial trend of fragmentation, shape and diversity landscape metrics to reflect the response of natural land cover to agricultural development. The six landscape indices on the landscape and basin scale indicate that the effects of agricultural expansion on regional natural systems have changed at different times. Li et al. (2015a, b) studied the relationship between landscape characteristics and water quality on the spatial and temporal scales. The Pearson correlation coefficient method was used to analyze the positive and negative effects of different "source–sink" landscape types on water quality, while the principal component analysis was used to select the landscape metrics and the multiple regression analysis model was used to analyze the relationship between landscape characteristics and water quality in every season. Considering the relationship between the spatial structure of land use and water quality, based on the land use types, landscape metrics and long-term water quality data, through statistical and spatial analysis method, Huang et al. (2016) found that most of the water quality parameters were negatively related to non-timber forest and urban areas but positively related to the forest area proportion. Shen et al. (2014) integrated multiple stepwise regression analysis and redundancy analysis methods to study the quantitative relationship between landscape metrics and water quality on landscape and class scales. The results show that the patch density of water, the maximum plaque metrics of forest and the proportion of unused land can effectively represent the landscape pattern on the impact of rainy season water quality. In addition, the article mentioned that the relationship between landscape pattern and water quality is more obvious when it rains. Li et al. (2015a, b) analyzed the influence of urbanization on water quality and analyzed the relationship between landscape ecological pattern and water quality by using landscape metrics. In the different regions, the relationship between the two is significantly different because there are differences in the hydrological situation and the process of nonpoint source pollution transmission. In the 16 catchment areas, Gonzales-Inca et al. (2015) studied the relationship between continuous water quality monitoring data and landscape pattern metrics in 21 years using statistical analysis of generalized linear model and multivariate redundancy analysis. The landscape pattern metrics reflect the information of watershed width, supersaturated zone and riparian zone; moreover, it is mentioned in the paper that the riverbank vegetation metrics are important indicators explaining the nitrate content in autumn.

According to the literature, the relationship between landscape pattern and water quality can be divided into two parts. First, it is the selection of landscape metrics and water quality indicators, and among them, the selection of water quality indicators should just be based on the quality of the water; there is no need to dwell on it. It is worth mentioning that the selection of landscape pattern metrics should be combined with certain methods. Most of the relevant research studies use the redundancy analysis method (Ouyang et al. 2014) to select independent landscape metrics, which reflects the different aspects of landscape structure. Second, the relationship between water quality indicators and landscape pattern metrics is analyzed by a stepwise regression method (Kariyeva and van Leeuwen 2011), the research of which is based on long continuous data.

In the research of the relationship between landscape pattern and water quality, this paper contends that the role of remote sensing has not been fully demonstrated. In terms of water quality monitoring, the existing water quality monitoring data are mostly derived from the measured data of the ground monitoring points, and this monitoring method is the most common and the best way to ensure the accuracy of the data. However, there are two drawbacks to the pattern of point monitoring: The first is that the monitoring point has a low degree of reflection on the overall situation of the basin. In the case of nonpoint source pollution, it is a continuous process in time and space. When contaminants are transported from the place of origin to the water and eventually flow along with the water, they are constantly accumulating. Compared with nonpoint source pollution, the data obtained by point monitoring can be regarded as a type of "sample" data, and the problem of data uncertainty will occur naturally when the sample data are used instead of the overall data. The second point is that the acquired data are restricted by the location of monitoring points. At a research scale, especially in the place where few people tread, nobody

Table 2 Brief comments of models

Model	Composition	Advantages	Shortcomings
SWAT	Hydrological process; nonpoint source pollution load; river pollutants transformation; water quality	Capable of modeling in the lack of data, predicting long-term effects	Systematic error in the daily simulation, and simplified reservoir calculus
AnnAGNPS	Hydrological process; erosion and sediment transport process; chemical substance module	Used to evaluate the best management measures	Incapable of distinguishing precipitation differences
HSPF	Pervious and impervious areas; hydrological module for a river or a completely mixed lake reservoir	Simulate the transfer and load of pollutants such as sediment and pesticide continuously	Low practicability and low spatial resolution
ANSWERS	Hydrological process; sediment transport process; nutrient transport process	Simulate the effect of land use on hydrology and erosion response	Incapable of simulating the subprocess of groundwater
SWMM	Single or long-term precipitation event simulation	Complete and applicable	More uncertain
WEPP	Climate generator; hydrological and irrigation process; surface runoff process; erosion process	Predict different land use methods, different time scale runoff, soil erosion and spatial distribution	No consideration is given to wind and gravity erosion

can ensure that there is a monitoring point at each junction. Therefore, the monitoring data are not comprehensive to a certain extent. However, the landscape pattern covers the entire watershed, and when analyzing the relationship between the two, there will be a problem that scholars hold a part as the whole.

As seen from the second chapter of the article, remote sensing has also had many achievements in the inversion of water quality data. After the successful extraction of water, compared to the point monitoring data, the surface monitoring data will be able to more fully reflect the water information obtained by using a remote sensing method to retrieve water quality indicators. According to the existing sensor band and inversion method, scholars can obtain reliable water quality inversion data in two ways. The first is to develop new sensors for water bodies and design special bands for important indicators (N, P content, etc.) that affect water quality. The second is to intensively study the water indicator inversion method. According to different water quality indicators, researchers should study the corresponding band algorithm to improve the inversion accuracy.

Application of environmental mathematical model in nonpoint source pollution

With the help of the environmental mathematical model, the analysis and prediction of water environment quality changes caused by landscape pattern changes have become the mainstream method of related research. Because of the complicated process and the inevitable relationship between the landscape pattern and the water environment quality, the limited research that focuses on the river's own situation can be improved with the help of an environmental mathematical model, and researchers can identify regional land use patterns and intensities at larger spatial scales. By establishing the correlation between landscape pattern and river biology, chemistry, hydrology and habitat, researchers can quantitatively simulate the influence of regional landscape pattern on the water quality of hydrological units. Some comments of environmental mathematical model can be seen in Table 2.

Using the export coefficient model and remote sensing technology, Wu et al. (2015) estimated the pollution load in the upper reaches of the Yellow River. The export coefficients were determined through the statistics (land use types, feces, sewage, livestock quantity), and the spatial distribution of nonpoint source pollution loads in the watershed was displayed based on GIS. Finally, the authors found that the nonpoint source load is not only related to the intensity of precipitation but also to the regional distribution of land use. Halal et al. (2014) proposed an adaptive platform for monitoring the water pollutants in the inland waters combined with remote sensing image data. This platform was based on supervised classification and statistical methods to construct intelligent watershed models and constructed the neural network model according to the spectral characteristics of the collected samples. Using this platform, the authors analyzed and predicted the distribution of nonpoint source pollutants in the watershed. Valent et al. (2016) studied the change of landscape pattern and its influence on hydrological processes. Through the remote sensing technology, the author classified the land use and quantified the influence of the landscape pattern change on the runoff in the watershed. Finally, based on the Wet Spa distributed hydrological model, the researchers analyzed the influence of the extreme precipitation event on the annual runoff.

Using the remote sensing data, Jordan et al. (2014) recorded the spatial and temporal changes of the landscape pattern and studied the effects of vegetation cover on soil erosion and total suspended matter content of the river, and he used the annual variation coefficient of the normalized vegetation metrics to quantify the change of landscape pattern. On this basis, the authors used a SWAT model to evaluate the monthly total suspended matter content and dynamic trend, and the spatial correlation of vegetation cover, landscape pattern, climate change and total suspended matter content was also analyzed by a linear regression model. In addition, some scholars have used the SWAT model to quantitatively analyze the influence of landscape pattern and climate change on hydrological processes and estimate the eutrophication of water bodies (Molina-Navarro et al. 2014). Based on this analysis and estimation, they studied the synergistic effect of climate and landscape pattern changes on basin flow and nutrient output. The results showed that chemical fertilizers and soil erosion were the main factors affecting the total amount of nitrogen and phosphorus, and the change of climate and landscape pattern had an obvious synergistic effect on the output of nitrogen and phosphorus in the watershed.

The above results can reveal the contribution of different land use patterns and spatial structure to the distribution of pollutants in various types of water bodies and indirectly reveal the chemical differences of pollutants in different landscape patches, thus providing the basis for nonpoint source pollution control and optimizing the various types of land use patterns and patterns on a regional scale. However, it should be emphasized that, regardless of the use of an environmental mathematical model, the establishment of the landscape pattern and water quality correlation does not represent a "causal" relationship. This is because the landscape metrics describe only the concept of a spatial layout, while the migration process of nonpoint pollutants in different landscape types is affected by many factors. In future research, scholars should further quantitatively analyze the mechanism of the interaction between the two on the basis of a qualitative description of the relationship. Considering the incorporation of the parameters (landscape pattern variables, basin hydrological topography parameters, precipitation conditions, etc.) into the environmental mathematical model, researchers can analyze the relationship between watershed landscape patterns and water quality from the point of view of nonpoint source pollution generation and migration.

Discussion

At the present stage of the landscape pattern research, this paper posits that there are still two shortcomings. (1) The aspect of classification based on remote sensing data. Compared with the continuous improvement of remote sensing data sources, the classification method has developed slowly. The use of only graph features or spectral features can no longer meet the classification requirements; the existing high-resolution and hyperspectral data provide a huge resource library, but the data processing methods cannot fully use these resources. Therefore, it is necessary to improve the existing classification scheme. On the basis of extracting the spectral information, the researchers should fully excavate the graphic features contained in the remote sensing image and combine the "map" and "spectrum" features (Luo et al. 2016; Feng et al. 2015) to perfect, supplement and optimize the classification scheme. (2) The aspect of landscape pattern metrics selection and innovation. After the "source–sink" landscape-type information is extracted, how to reflect the pattern information is another research point. Using landscape metrics to reflect the landscape information is the mainstream of the existing research method. Compared with the traditional remote sensing metrics, such as NDVI, the landscape pattern metrics calculation result is obviously not spatial, and the use of a numerical result to reflect regional landscape pattern information results in the absence of landscape heterogeneity. In addition, the existing landscape pattern metrics are mostly analyzed from the perspective of the shape, distribution and aggregation of landscape patches, which is an independent calculation process and not related to the specific ecological process. In the research of landscape pattern, the relationship between pattern and process is emphasized, while the traditional landscape metrics can only reflect the pattern, not the process. In the future, concerning the characteristics that high time resolution remote sensing sensors can obtain continuous images for in the experimental area, the landscape pattern research should be related to the specific ecological process and then study the specific ecological process hidden behind the landscape pattern.

In the research of the relationship between landscape pattern and water quality, the breakthrough point of the research is to seek the relationship between metrics and specific water quality indicators. Researchers first use the correlation analysis method (Spearman rank correlation, etc.) to select the independent landscape metrics to reflect the landscape pattern information and then use the stepwise regression and redundant sort method to analyze the relationship between the landscape metrics and the water quality metrics in which the water quality data are obtained either by the monitoring station or by the hydrological model. The correlation between the water quality indicators and the landscape pattern metrics can partly reflect the relationship between the "source–sink" landscape pattern and the nonpoint source pollution to a certain extent. However, there are some shortcomings in the process of determining the relationship, and the inadequacies are as follows. (1) The landscape metrics can reflect the landscape information to a certain extent, but the landscape index has some defects in the quantitative extraction of the pattern information. For example, when the composition of the landscape pattern remains unchanged, while the spatial composition of the landscape changes, the results of the landscape metrics may not reflect this change. (2) The effect of landscape pattern on water quality index is lagging. The process of nonpoint source pollutants being transported from the output to the river requires different times in different situations, so when the researchers obtain landscape information at a certain time, the question should be verified that when the measured water quality data should be selected.

The quantitative model of nonpoint source pollution based on remote sensing technology has many advantages, but because the two technologies are developed separately, there are still some shortcomings in the integrated application. First, because the standardized parameters required by remote sensing technology are large, when the nonpoint source pollution simulation is carried out in watersheds of different scales, the statistics of the watershed will not meet the model requirements. Second, there are few powerful professional statistical analysis modules that can simulate nonpoint source pollution conveniently and flexibly. Rather than embedding the model into the kernel of the remote sensing technology, the relationship between the model and the remote sensing technique is only a loose combination. In addition, the analysis for the time domain of the model by remote sensing technology is not strong enough, so the simulation results will be subject to certain restrictions. Third, when the remote sensing technology is used to establish the nonpoint source pollution quantitative model, the characteristics of remote sensing data (phase, resolution, clarity, etc.), the choice of software and the detail level of reference information source are very important for the accuracy of the nonpoint source pollution quantitative model. However, there are still some deficiencies in the current research, such as the low accuracy of remote sensing data, the lack of an effective inversion model and other issues, and many features related to nonpoint pollution information of the spectrum have yet to be further developed.

Conclusion

In view of the characteristics of the macroscale and multiscale of remote sensing, the analysis of landscape patterns is the basis for the study of the relationship research between patterns and ecological processes, and it is also the key to the study of landscape dynamics and functions. However, the uncertainty in the process of landscape pattern information extraction and landscape metrics calculation limits the research of landscape patterns and nonpoint source pollution to a certain extent. It is gratifying that, with the continuous development of remote sensing technology, especially the launch of high-resolution sensors, this problem is tending to be solved. Using remote sensing and GIS techniques, researchers can obtain more accurate data that are consistent with the actual ground situation, which is essential for research on landscape patterns and nonpoint source pollution. Future landscape pattern and nonpoint pollution analysis research should focus on four aspects. (1) Improving the classification method. The classification process should emphasize the combination of graphical features and spectral features, and the specific classification scheme should be established according to the different ecological characteristics of the research area. (2) Improving the landscape pattern metrics. The results of the metrics should reflect the characteristics of ecology and heterogeneity. (3) The quantitative calculation process of nonpoint pollution should learn from Big Data processing techniques, and the multi-source data in the calculation process should be processed in a cooperative manner. (4) Emphasis on the interdisciplinary research between remote sensing, GIS and landscape ecology.

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Compliance with ethical standard

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