The Potential of Integrating Landscape, Geochemical and Economical Indices to Analyze Watershed Ecological Environment

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Abstract:

A river watershed is a complicated ecosystem, and its spatial structure and temporal dynamics are driven by various natural factors such as soil properties and topographic features, human activities, and their interactions. Thus, characterizing the river watershed ecosystem and monitoring its dynamics is very challenging. In this study, we explored the characteristics of the ecosystem and environment of Yalong River watershed in Ganzi Tibetan Autonomous Prefecture, Sichuan Province of China by analyzing and modeling the relationships among economic indices, heavy metal elements and landscape metrics. Landsat 8 data were used to generate a land cover classification map and to derive landscape pattern indices. Governmental finance statistics yearbook data were referred to provide economic indices. Moreover, a total of 9 water samples (interpolated to 30 samples) were collected from the upstream to the downstream to obtain the values of heavy metal concentrations in the water body. Then, both correlation and regression analyses were applied to analyze and model the relationships among these indices. The results of this study showed that 1) The ecological status and process of this river watershed could be explained by analyzing the relationships among the economic indices, heavy metal elements and landscape pattern indices selected based on correlation analysis; 2) The accumulated economic indices were significantly correlated with Al, Fe and Ni and should be applied to the integrated assessment of the watershed ecological environment; 3) Cu, Zn and Pb were the main elements that showed significant correlations with the forest land; 4) Some landscape patterns indices such as TA and MESH could be used to the integrated assessment of the watershed characteristics because of their strong correlations with the area (or area percentage) of important landscape types; and 5) transportation land had a close relationship with per capita GDP. This study implied that analyzing and modeling the relationships among the economic indices, heavy metal elements and landscape pattern indices can provide a powerful tool for characterizing the ecosystem of the river watershed and useful guidelines for the watershed management and sustainable development.

Keywords: Watershed; geochemistry; landscape; economic indices; remote sensing; statistical analysis.

1. Introduction

The challenge of balancing human needs for water with environmental sustainability has come to a head in river systems, where various management plans to conserve and manage the ecosystems have been thrown into a turmoil (Pincock 2010). River ecosystems are mainly influenced by integrated biological, chemical and physical subsystems, which increases uncertainty in ecological assessments, and hampers prediction for the ecological environment changes (Wiley et al. 2010). An in-depth understanding of ecological status and process in river systems is very important for river conservation and management (Wang and Yang 2014). Stream flow and water quality of a river are affected by both natural and anthropogenic factors that exist within a watershed, hence the watershed has been recognized as an appropriate analysis unit for addressing the challenges of water management (Singh et al. 2014; Deng et al. 2014).

There is an urgent demand for sustaining or improving the functions of watersheds to strengthen their roles in supporting human and meeting ecosystem needs simultaneously, because watersheds provide economic goods and ecological services that impact the livelihoods of people (Ingram et al. 2012). Benefiting the economy, community and environment synchronously would realize the sustainable development of a watershed. To achieve this goal, a proactive approach that combines information of economic, social and ecological influence is needed (Randhir and Shriver 2009; Kantamaneni 2016). Thus, the opportunity for sustaining human and their river systems can be enhanced by examining how socioeconomic and ecological processes are integrated at the watershed level (Wolters and Kuenzer 2015; Naiman 1992).

Human activity induced disturbances are one of the most important factors that generate potentially permanent changes to the ecological structure and functions of watersheds (Wang et al. 2015). The pattern and process of land use (or land cover) is one typical manifestation of the interaction between human activities and ecological processes observed in a region (Naiman 1992). Both the extent and depth of transformation are determined by regional land use patterns and processes (Kabat et al. 2004). Understanding how human depends on landscape functions and products, and how land use affects ecological and socioeconomic processes can provide a sound basis for guiding sustainable development of a watershed (Naveh and Lieberman 1984; Zonneveld and Forman 1990).

Landscape ecology is a subsidiary discipline of modern ecology, which deals with the interrelationship between human and landscapes that they live on (Naveh and Lieberman 1990). Landscape ecology focuses on the interactions between landscape patterns and ecological processes, and exploring the impacts of land use patterns on water quality and the spatial scales over which these effects are manifest has become a significant theme of landscape ecological studies (Turner et al. 2001). Digitized land use data stored in a Geographical Information System (GIS) are always used to conduct the analysis of landscape patterns, especially, landscape-level ecosystem status can be credibly estimated through landscape measurements based on land use data obtained from remote sensing imagery (Johnson and Patil 2006). However, as the landscape patterns and ecological processes interact in diverse ways, neither of them can be ignored to grasp the synthetical dynamics of the environment (Fu and Jones 2013). Although various factors including social, economic, and ecological considerations that interactively determine landscape patterns are known abstractly, the quantitative interrelationships among these variables are inadequately recognized. Furthermore, it is difficult to describe the behaviors of a landscape scaling up from ecological systems to communities, thus in-depth exploration of the relationships between landscape patterns and ecological processes is necessary. Because a landscape presents macroscopic and vast scale characters, which cannot be described and studied at a microscopic level, the landscape and geochemistry interaction will be a crucial challenge for studying on the ecological environment assessment in the coming decades. For example, many recent studies have focused on the influence of land use patterns in watersheds on water quality and biological communities in streams (Vrebos et al. 2017; Vaighan et al. 2017; Dzinomwa and Ndagurwa 2017).

Geochemistry is the study of the distribution and migration of elements in the environment where we live in, aiming at exploring the distribution of elements in the earth and interpreting the processes that induce these distribution patterns based on techniques and principles of chemistry and physics (Wainerdi and Uken 1971). Hydro-geochemical investigations of surface water can provide information on the extent and degree of element impacts so as to estimate the level of pollution and identify principal pollutants in surface water (Quercia and Vidojevic 2012). Hydro-geochemical speciation methods can offer a more realistic and reliable measure to identify the degree of migrated water contamination, because they provide fundamental ideas for better understanding of water features and they have a sophisticated and meticulous methodology (Moldan 1992; Reuther 1996). However, the transportation of particulate and dissolved materials in river systems is a complicated action of different biological, chemical and physical processes occurring in the watersheds and in the water (Hedges et al. 1986). Hence, available information on trace elements, including heavy metals in water, is generally inadequate for regional studies of the ecological environment, and little systematic information on the spatial relationships between geochemistry and ecology of water is available (Bowie and Thornton 1985). Thus, a fundamental question concerns whether we can detect, describe and predict the ecological effects at the geochemical level has been proposed (Reuther et al. 1996). Then, applying landscape and geochemistry integrated methods to analyze the ecological environment of a watershed has its theoretical basis and practical need. Furthermore, socioeconomic and ecological processes need to be combined to obtain a sustainable development of a watershed at the landscape level, on which all kinds of analyses utilize land cover types as the basic unit of calculation.

First of all, landscape pattern indices, characterizing diversified aspects of composition, structure and spatial configuration of landscapes, were introduced to quantitatively describe the correlations between spatial patterns and ecological processes (O'Neill et al. 1988; Remmel and Csillag 2003). One of the most fascinating features of landscape pattern indices is the simplicity: large amount of data can be summarized by a single number (or by a limited set of numbers) without a priori knowledge about the processes and organisms of landscapes (Fortin et al. 2003). Besides, heavy metals are especially dangerous elements and expose potential ecological risks to living organisms, on account of their bioaccumulation, non-degradability and toxicity features (Cai et al. 2015). Heavy metal contamination in aquatic ecosystems is frequently surveyed by evaluating concentrations in sediments, biota and water (Rahman et al. 2014), in which variations of the heavy metal distributions can provide direct information for evaluating the status of pollution and baseline data to help further develop an efficient strategy on their controls (Dong et al. 2015; Yeh et al. 1977). Apart from that, economic indices provide supplementary information on the strength of human activities that give rise to the production of pollutants (Zhou et al. 2012). For example, the Gross Domestic Product (GDP) is commonly used as an index for evaluating the economic health and measuring the living standard of a country. Because the sustainable development of watersheds requires an integration of hydrologic, ecological and socio-economic aspects, relationships among these indices or indicators involving landscape pattern, geochemistry and economy need to be explored to gain an in-depth understanding of ecological processes and properties in a watershed.

The main goals of this study are to: (a) analyze whether and how the relationships among these indices including landscape pattern, geochemistry and economy can be found, and (b) explore the potential of analyzing the ecological environment of a watershed based on a landscape, geochemistry and economy integrated view.

2. Materials and Methods

2.1 Study area and sampling

The study area was Yalong River watershed, within Ganzi Tibetan Autonomous Prefecture, Sichuan Province (Fig. 1). The study area has a total area of 70,366 km^2, and 3/5th of the Yalong River's full length is distributed in the study area. This region is located in the upstream section of the Yalong River, which has an important influence on the water quality and ecological environment. Covering a total of six counties including Shiqu, Dege, Ganzi, Xinlong, Litang and Yajiang in the administrative regions of Ganzi, most of the area is mountainous with steep terrain. In Shiqu County located in the upstream of the basin, the average elevation is 4526.9 m, the average annual temperature is below -1.6 ℃, and the average annual precipitation is 569.6 mm. However, in Yajiang County located in the downstream of the basin, the lowest elevation is 2266 m, the average annual temperature is below 11 ℃, and the average annual rainfall is 650 mm. The regional vertical variations of temperature, precipitation, and vegetation are obvious with the terrain height changes (Shen et al. 2010; 2012).

In total, 9 water samples were collected in the study area in 2014 (Fig. 1). The sampling locations were steadily scattered in the study area from its upstream to downstream to survey heavy metal concentration characteristics in the water body. A hand-held global positioning system (GPS) receiver was used to record the exact locations of the samples for further being imported into ArcGIS. In order to perform the parametric statistical analysis, 30 observation points were obtained through the interpolation of 9 water samples. Furthermore, an identify function of ArcGIS was used to acquire the data of landscape pattern and economy indices for statistical analysis based on the 30 observation points.

2.2 Measuring landscape pattern metrics

2.2.1 Source of data

This study collected and used six multi-spectral bands (band 2-blue, band 3-green, band 4-red, band 5-near infrared, band 6-shortwave channel 1, and band 7-shortwave channel 2) of Landsat 8 images at the spatial resolution of 30 m × 30 m to classifying land cover types of this study area and obtain land cover maps. A total of nine cloud-free leave-on and leave-off images dated from May of 2013 to Jan. of 2014 were acquired by downloading from the website supported by USGS (United States Geological Survey). The radiometric correction and geometric correction of the images were first conducted and then were clipped according to the boundary of the study area with ENVI software.

2.2.2 Land cover classification

The establishment of a scientific land cover classification system according to the regional condition is the primary work needed to obtain the regional landscape data (Anderson et al. 1976; Li and Ma 2000; Bazi and Melgani 2006). Reference for the classification system was made to the land use and land cover classification system for remote sensing data from USGS, the national land classification (For Transition Period) from Ministry of Land and Resources of P. R. China, as well as the regional condition of land cover in the Yalong River watershed, and the requirements for further study. The regional landscape was classified into: forest, river, grassland, lake, marsh land, bare soil, farm land, human habitation, industrial land, glacial and snow, and transportation land.

Based on the Yalong River watershed land cover classification system, a strict description for each type of land cover class was obtained. An object-oriented classification method was applied to extract the land cover information of the study area. Unlike the traditional classification methods that analyze spectral information of land cover types, the object-oriented classification method accounts for the spatial characteristics such as shape and compactness of objects and the relationships between the objects (Sapozhnikova et al. 2006; Kassouk et al. 2014). This method first carried out multi-scale image segmentation, that is, classified the pixels into homogeneous polygons (objects) based on their similarity measured using variances of pixel values, and shape, smoothness and compactness of objects. The classification of land cover types was then conducted using decision tree and nearest neighbor. In order to improve the accuracy of the classification, expert knowledge was applied to conduct the verification and interpretation.

2.2.3 Obtaining land cover map

Based on the above methods, this study obtained the land cover map of the Yalong River watershed (Fig. 2). In accordance with the statistics of the classification results, the areas and proportions of the land cover types of the landscape were obtained, as shown in the Table 1. The statistics showed that the grassland and forest were the major land cover types with their area accounting for 89% of the entire watershed. As shown in Fig. 2, the land cover map of the Yalong River was smooth and compact due to the segmentation of the objects, without the traditional 'salt and pepper' phenomenon formed by isolated pixels. Also, the segments contained information such as shapes, veins, space, and so on, which could be comprehensively utilized in the process of the classification.

In this study, a 30 m spatial resolution image was used in the classification. To ensure the results of the classification accuracy assessment were objective, the samples used for the accuracy assessment were selected from the 1 m spatial resolution image provided by Google Earth. A total of 450 samples were obtained by a simple random sampling method, and these samples were used to calculate the confusion matrix (Foody 2002). The overall accuracy of the classification was 87.11%, and the Kappa coefficient was 0.855. Therefore, the high accuracy could fully meet the demand of this study.

2.2.4 Computing landscape pattern metrics

Landscape pattern indices are easy to understand due to their ecological meanings. The indices also contain certain statistic characteristics and are easily used to analyze and compare the sizes of different patches, and provide important information of landscape patterns, structures and spatial composition to explain the functions of landscapes. Landscape pattern indices have been widely used to describe landscape patterns and changes, and to set up the contact between the patterns and landscape processes (Turner et al. 2001).

Considering the aims of this study and the features of every landscape pattern index, the follow indices were chosen as the indicators to quantify the ecological features: Total Area (TA) represents the area of each landscape type; Total Edge (TE) equals to the sum of the edge lengths of all the segments involved in a corresponding patch type; Edge Density (ED) means the sum of the edge lengths of all segments involving a corresponding patch type and divided by the total landscape area; Contagion (CONTAG) is the negative sum of the proportional abundance of each patch type and multiplied by the proportion of the adjacencies between the cells of this patch type and another patch type; Percentage of Like Adjacencies (PLADJ) is computed as the sum of the diagonal elements of the adjacency matrix and divided by the total number of adjacencies; Interspersion & Juxtaposition Index (IJI) considers all the patch types present on an image to analyze the amount of patch adjacency or fragmentation; Patch Cohesion Index (COHESION) is computed from the information contained in the patch area and the perimeter; Landscape Division Index (DIVISION) is defined as the probability that two animals placed within different areas somewhere in the region of the investigation might find each other; Effective Mesh Size (MESH) simply denotes the size of the patches when the landscape is divided into S areas, with the same degree of landscape division as obtained for the observed cumulative area distribution; Splitting Index (SPLIT) is defined as the number of patches obtained when the total landscape is divided into the patches of equal size, in such a way that this new configuration leads to the same degree of landscape division as obtained for the observed cumulative area distribution; Shannon's Diversity Index (SHDI) is the representative of diversity of a landscape; Number of Patches (NP) reflects the number of all the landscape patch types; Patch Density (PD) measures the heterogeneity of the landscape; Largest Patch Index (LPI) indicates the influencing extent of the largest plaque for the entire landscape; Landscape Shape Index (LSI) reflects the divergence of the shape of landscape patches from the ideal circle; and Aggregation Index (AI) means the percentage of like adjacencies between cells of same patch type (McGarigal et al. 2012).

2.3 Measuring chemical concentration

The chemical parameters (Al, Fe, Cr, Ni, Cu, Zn, Cd, Pb) were measured according to the industry standard (DZ/T0064-93) (Figs. 3-6), conducted by Ministry of Geology and Mineral Resources of P. R. China. All these elements were measured with a method of ICP-MS (Inductively Coupled Plasma Mass Spectrometry).

2.4 Measuring economic variables

The GDP and Population are commonly used as the indicators for measuring the economic health and living standard in a country. In addition to these two indices, other indices are also used to observe the effects of human disturbances on water quality. Data pertaining to spatial distribution of economic indices (Population, Accumulated Population, Population Density, Accumulated Population Density, GDP, Accumulated GDP, Per Capita GDP, Accumulated Per Capita GDP, Gross Output Value of Agriculture, and Accumulated Gross Output Value of Agriculture) were generated through the spatial analysis methods, to identify the relationships between economic indicators and other indices. As examples, Fig.7 and Fig. 8 respectively showed the spatial distributions of GDP and its accumulation values. The accumulated indicators were calculated by summing the local values of the corresponding indicator along the river from the upper reach and implied the impacts of accumulated values.

2.5 Statistical analysis

Due to a large number of variables of interest (VIs), we first clustered the VIs in terms of their Pearson correlation coefficients (Pearson 1895), and then, the linear regression was performed on those highly correlated VI clusters. In this study, an agglomerative hierarchical clustering analysis (HCA) was used to assess the strength of linear correlation. HCA builds up the clustering hierarchy from bottom to top, i.e., each VI starts with being its own cluster, and the pairs of clusters are then merged as one moves up. The merge happens if the dissimilarity of a pair of clusters is the local minimum. HCA generates a graphical representation – a dendrogram (or tree) – where the VIs are hierarchically grouped together in the hierarchical fashion (e.g., Fig. 10). The height of the dendrogram (tree) implicates the level of dissimilarity, and the process of cluster detection is referred to branch pruning at a desired height (Langfelder et al. 2008). For clustering the strength of linear correlations on VIs, the dissimilarity matric used in the 1st HCA was the determination of Pearson correlation coefficient, r^2. The tree was cut at the dissimilarity level of 0.1 (r^2=0.9), where the corresponding correlation coefficient would then be larger than 0.949 or smaller than -0.949 in order to maintain the statistical significance.

In addition, stepwise regression was also used to identify the interrelationships among the landscape pattern, heavy metal elements and economic indices, and to determine whether and how the relationships among them could be presented by specific representative factors. The optimal models were assessed based on the coefficient of determination (R^2) and statistical significance (Sig.).

3. Results and discussion

3.1 Distribution characteristics of elements in water samples

Figures 3-6 show the values of water quality parameters for the upper, middle, and lower main channels. The contents of Cr, Ni, Cu, Zn, Cd, and Pb were all below the guideline values for Drinking-water Quality defined by World Health Organization and the Environmental Quality Standards for Surface Water by the Ministry of Environmental Protection of P. R. China. However, the contents of Al and Fe were significantly higher than the guideline values. Spatially, the contents of the elements in the river water generally increased from the upper to downstream. The average values of Al, Fe, Ni, Zn and Pb continuously increased as the water flew to the downstream. The spatial pattern is somewhat alike to that gained in the study of the Fuji River in Japan, in which high-pollution regions were mainly located in the downstream (Shrestha and Kazama 2007). However, the spatial distributions of Cr, Cu, and Cd values fluctuated from the upstream to the downstream.

3.2 Analysis of landscape pattern

Based on the land cover classification results, the landscape pattern indices of the study area were obtained using Fragstats 4.2 software, which are shown in Table 2. The results indicated that the values of the indices were diversified from the upstream to the downstream except PLADJ, AI, COHESION and MESH. Among the indices, TA, LPI, CONTAG, PLADJ, COHESION, MESH and AI showed the highest values, while PD, ED, LSI, DIVISION, SPLIT and SHDI had the lowest values in Shiqu county located in the upstream, implying that a health ecological condition was observed in the upstream. In Xinlong county located in the midstream, there were highest values for NP, PD, TE, ED, LSI, DIVISION, SPLIT and SHDI, and lowest values for LPI, PLADJ, IJI and AI, demonstrating that the ecological environment was disturbed and landscape fragmentation was observed. The landscape indices LPI, PD and DIVISION showed a turning point in the midstream Xinlong County. In Litang county that had a smallest area, the values of TA, NP, TE, CONTAG, COHESION and MESH were lowest, while the value of IJI was highest, indicating that the ecological environment needed to be paid attention to.

The AI in all the counties had the values of above 91.5, indicating that the landscape of the study area showed a high degree of aggregation, that is, the ecological environment was still in a good condition. The differences of LPI between the counties were very obvious. All the high values were distributed in the upstream, which meant the large patches dominated the landscape of the region. LSI had the higher values in the downstream, which indicated that the landscape structure was complicated in this region. In addition, by combining the values of CONTAG, PLADJ, COHESION, DIVISION, MESH, SPLIT and SHDI indices in the table, it was found that the upstream had a better but weaker ecological condition than the downstream.

3.3 Correlations among landscape pattern, geochemistry and economy indices

3.3.1 Clustering correlation on VIs

To construct the HCA, a dissimilarity matrix requires to be defined. For the assessment of linear correlation among all the VIs, the dissimilarity was defined as $1-r^2$. The linear dissimilarity matrix was exhibited as a color map in order to visualize the correlation strength (Fig. 9). On the map, the cell color indicates the correlation strength between the pairs of VIs, and as it shifts from blue to red, the linear correlation gets stronger. The HCA for linear correlation resulted a dendrogram shown in Fig. 10, where the red dash line was the threshold at which the tree was pruned. As mentioned before, the threshold was 0.1 in order to maintain the statistical significance. Therefore, only the clusters below 0.1 (red dash line in Fig. 10) were proceeded to further investigation (Table 3).

3.3.2 Regression models of heavy metal elements, landscape pattern and economic indices

Table 3 shows that the members of cluster 1 are chemical elements, the members of cluster 3 and cluster 4 are landscape pattern indices, the members of group 6, 7 and 8 are landscape area statistical indicators, and the members of group 10 are all economic indicators. It is reasonable and easy to understand that the same categories of indicators are clustered in the same group. However, we are concerned about whether there are correlations among different categories of indicators and what quantitative relationships exist between them. Therefore, we explored the regression models between different categories of indices in group 2, group 5 and group 9, respectively. Furthermore, the relationships between geochemical elements and other indicators are what we want to see. Therefore, the regression analysis of each chemical element in group 1 and all other types of indicators was also separately conducted.

The stepwise regression greatly reduced the impacts of multi-collinearity in this study. All the obtained models were significant at the significant level of 0.05 (Table 4). There was only one variable accumulated per capita GDP in the models for the Al element. The variables accumulated per capita GDP and human habitation percentage were involved in the model for the Fe and Ni element. It was found that as the indicators of the economic health in a country and the references for quantifying the intensity of human activities, the economic indices had significantly linear relationships with the Al, Fe and Ni elements at the significant level of 0.05. Furthermore, the accumulated economic indices were involved because of the assembling characteristics of elements from the upstream to the downstream (Cortecci et al. 2009; Li and Zhang 2010; Taylor et al. 2012; Yang et al. 2014; Bu et al. 2016).

The model for the Cu selected the variable forest percentage because of its significant correlation with the element. Two variables forest percentage and transportation land percentage were highly correlated with the Zn element and involved in its prediction model. Cu and Zn are crucial elements for both animals and plants, but they have also been identified as possible specific pollutants in many countries (Comber et al. 2008; Jensen et al. 2016). Many studies have proved that the distribution patterns of Cu and Zn have significant correlations with certain landscape patterns and processes (Stone and Droppo 1996; Lindström 2001; Morse et al. 2016). This was supported by the results of this study.

The variables forest and forest percentage were involved in the model for the Pb element. Forest had a significantly negative correlation with Pb, which is intelligible because forest land has important ecological value and Pb is greatly influenced by human activities. Moreover, the landscape pattern variable TA were sensitive to the land cover area due to the calculation principle and three variables marsh land, marsh land percentage and river that reflect the distribution of landscape area were included in the model. The variables transportation land were involved in the model for the landscape pattern variable MESH. The MESH was used to measure the spatial distribution and degree of landscape fragmentation in former study because it has been proposed as a good single indicator of land division by roads (Jaeger 2000, Li et al. 2010).

A linear relationship between transportation land and per capita GDP could be observed because of both of them involving in the model. Transportation land was highly correlated with the economic index because the traffic condition was one key factor for supporting the local human activities (Gentile and Noekel 2016; Alam et al. 2016). However, no significant correlations were observed between heavy metal elements and landscape pattern indices, which indicates the limitation of analyzing the relationships between the heavy metal elements and the landscape pattern indices to explore the ecological status and process.

4. Conclusions

In this study, the relationships between the economic indices, heavy metal elements and landscape pattern indices were explored and used to analyze and characterize the ecosystem and environment of Yalong River watershed within Ganzi Tibetan Autonomous Prefecture, Sichuan Province, using water samples collected in the field and an image derived land cover classification. In summary, this study led to following findings: 1) The ecological status and process of the watershed could be explained by analyzing the relationships among the economic indices, heavy metal elements and landscape pattern indices selected based on correlation analysis; 2) The accumulated economic indices were significantly correlated with Al, Fe and Ni and should be applied to the integrated assessment of the watershed ecological environment. This conforms to the assembling characteristics of the elements in the river from the upstream to the downstream; 3) Cu, Zn and Pb were the main elements that showed significant correlations with the forest land and this was also supported by previous studies; 4) Some landscape patterns indices such as TA and MESH could be used to the integrated assessment of the watershed ecological environment because of their strong correlations with the area (or area percentage) of important landscape types, i.e., river, marsh and transportation land; however, some limitations of using the landscape pattern indices were also observed, indicating that the selection of the landscape pattern indices was essential; and 5) transportation land had a close relationship with per capita GDP because transportation and mobility were vital constituents of socio-economic development in any country. The conclusions will play a fundamental role in establishing the synthetic models for management of watersheds.

However, it was found that the connection between the economic development and the landscape structure was unable to be established with a simple index analysis. Moreover, analyzing the relationships between the heavy metal elements and the landscape pattern indices to explore the ecological status and process had their limitations. The ecological problems of a watershed could not be revealed through simply analyzing one kind of indices and the sustainable development of the watershed requires an integrated evaluation of hydrologic, ecological and socio-economic factors. A more complicated and comprehensive approach is needed to get an in-depth understanding of the ecological processes and properties of the watershed. Although, at the present, an increasing number of theories and methods for integrated watershed management have been developed, the exploration of quantitative relationships among the driving factors still requires a significant effort and multivariate statistical methods based on sufficient sampling data in the future work could be an alternative.

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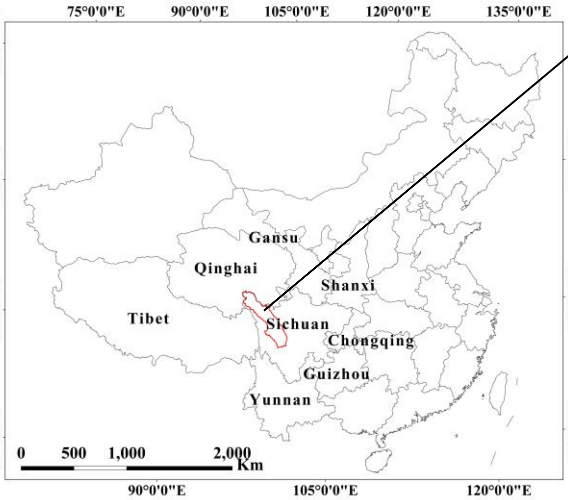

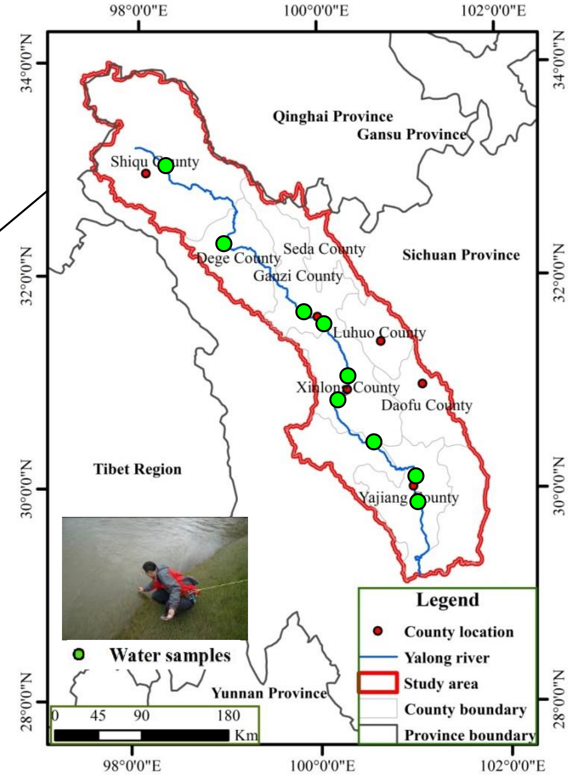

Fig. 1. The study area and its location.

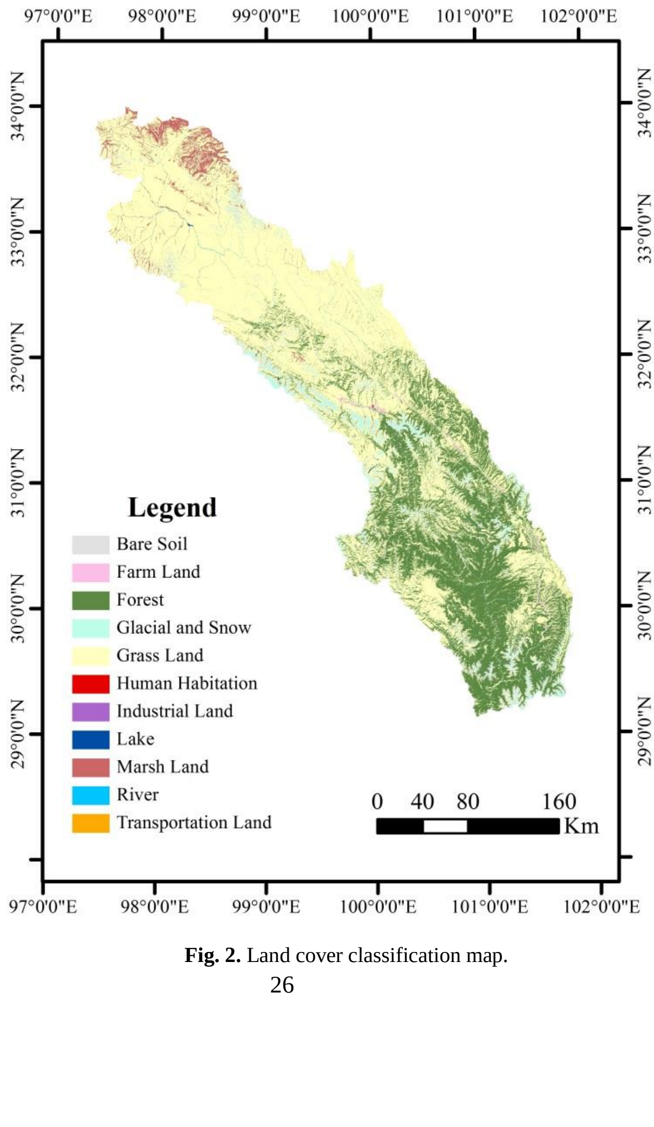

Fig. 2. Land cover classification map.

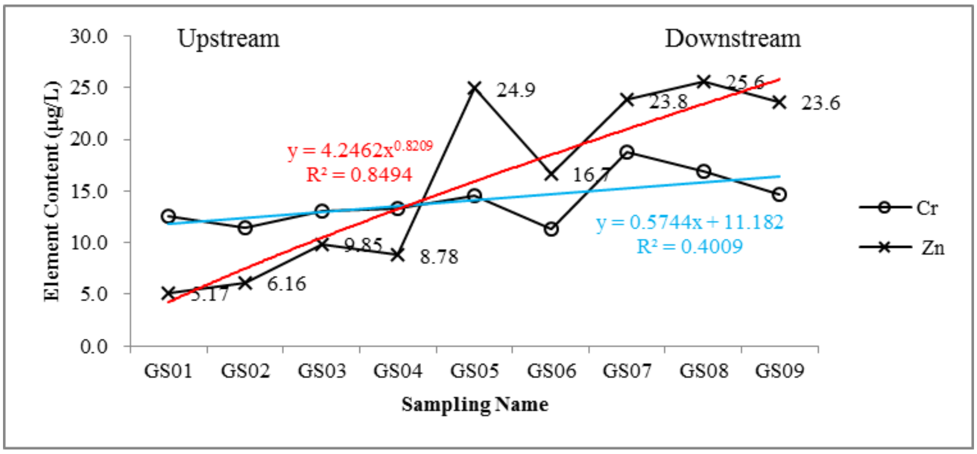

Fig. 3. The values of Cr and Zn elements from water samples along the river from upstream to downstream (μg/L)

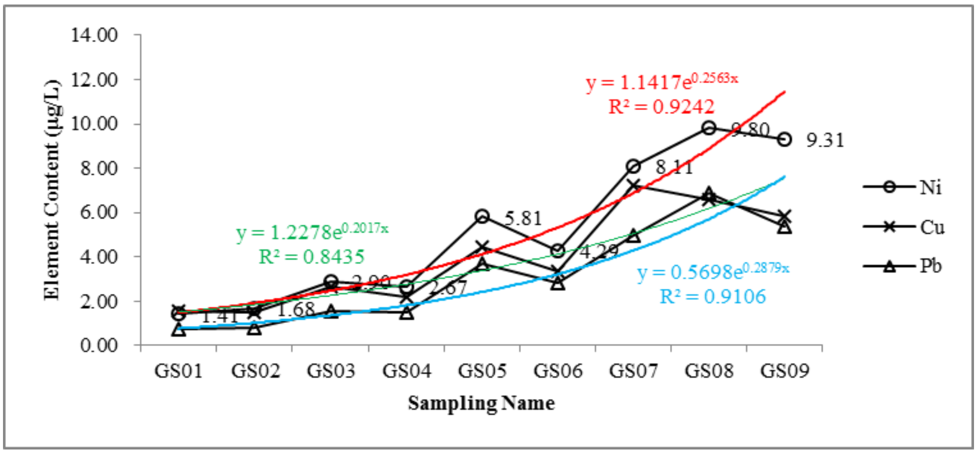

Fig. 4. The values of Ni, Cu and Pb elements from water samples along the river from upstream to downstream (μg/L)

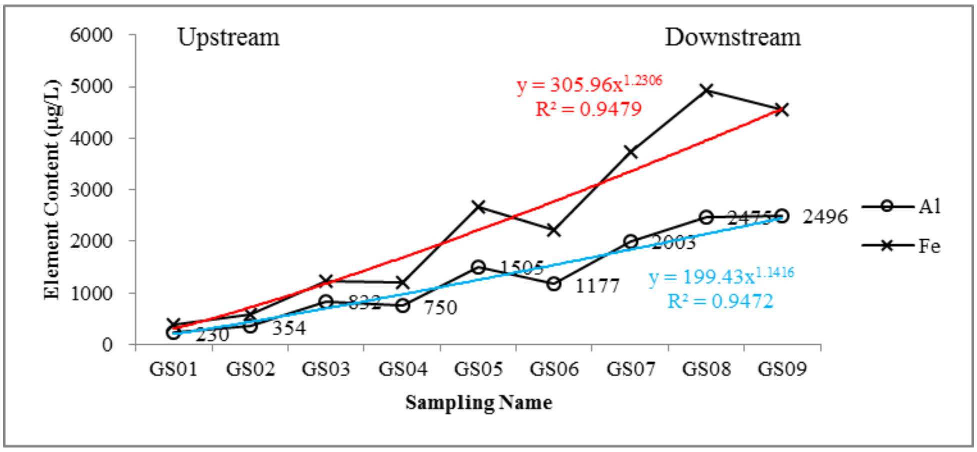

Fig. 5. The values of Al and Fe elements from water samples along the river from upstream to downstream (μg/L)

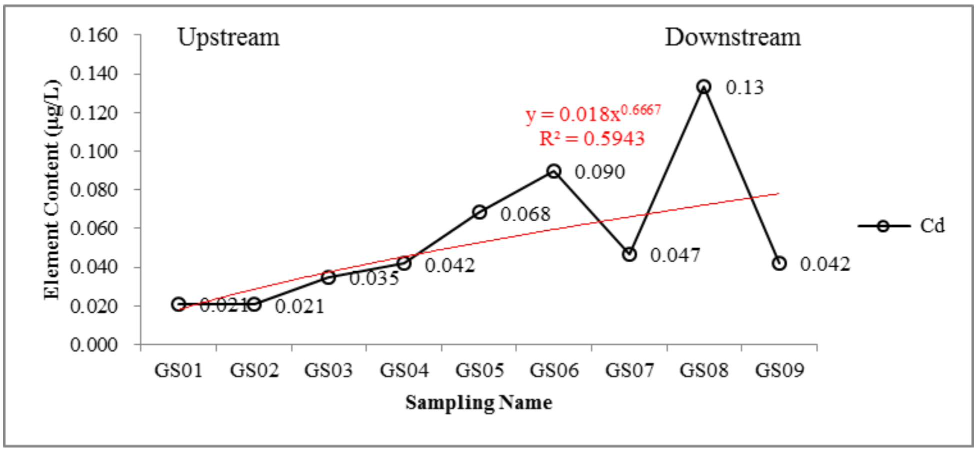

Fig. 6. The values of Cd element from water samples along the river from upstream to downstream (μg/L)

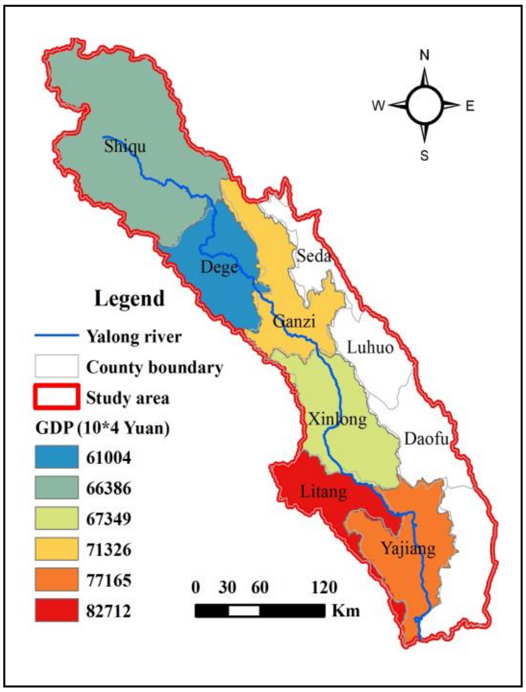

Fig. 7. Map showing the GDP of the counties that the river goes through

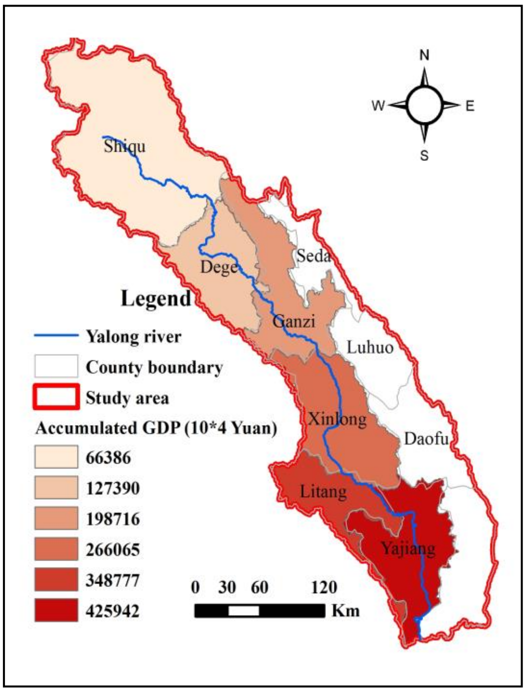

Fig. 8. Map showing the accumulated GDP of the counties that the river goes through

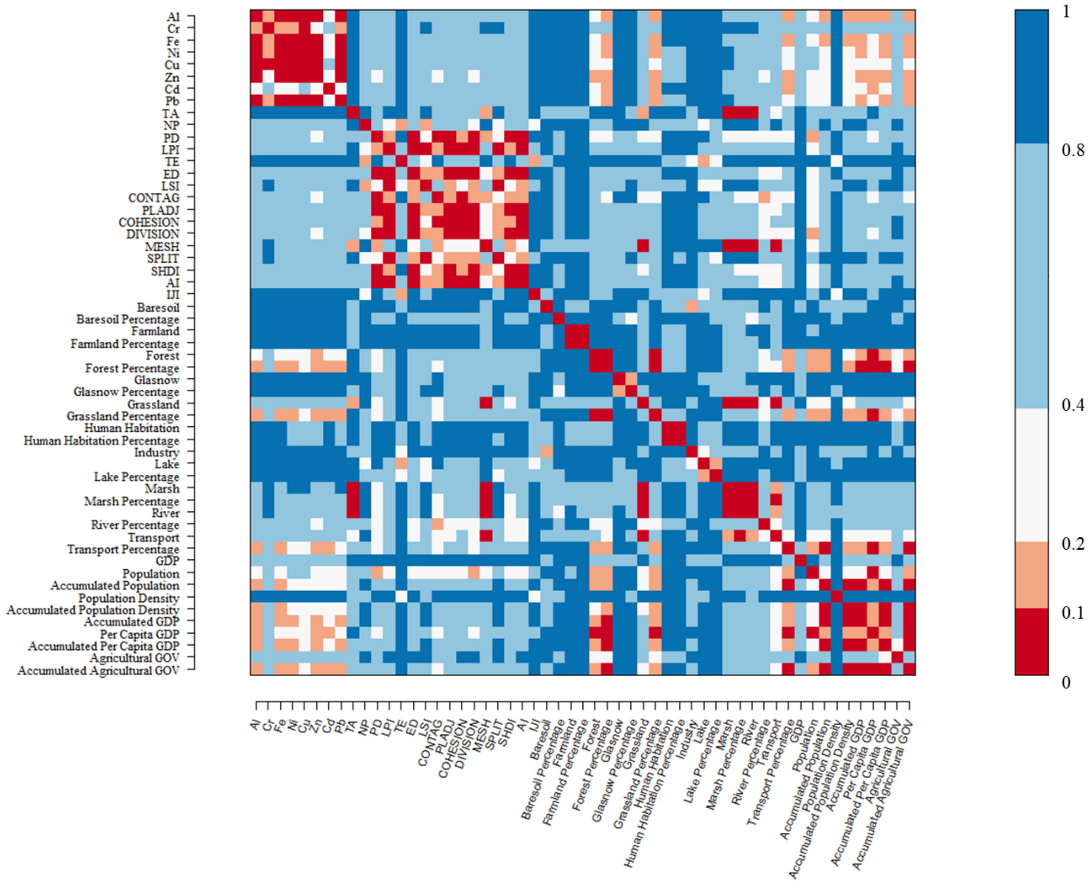

Fig. 9. The color map for visualizing the dissimilarity matrix measured by 1-r^2.

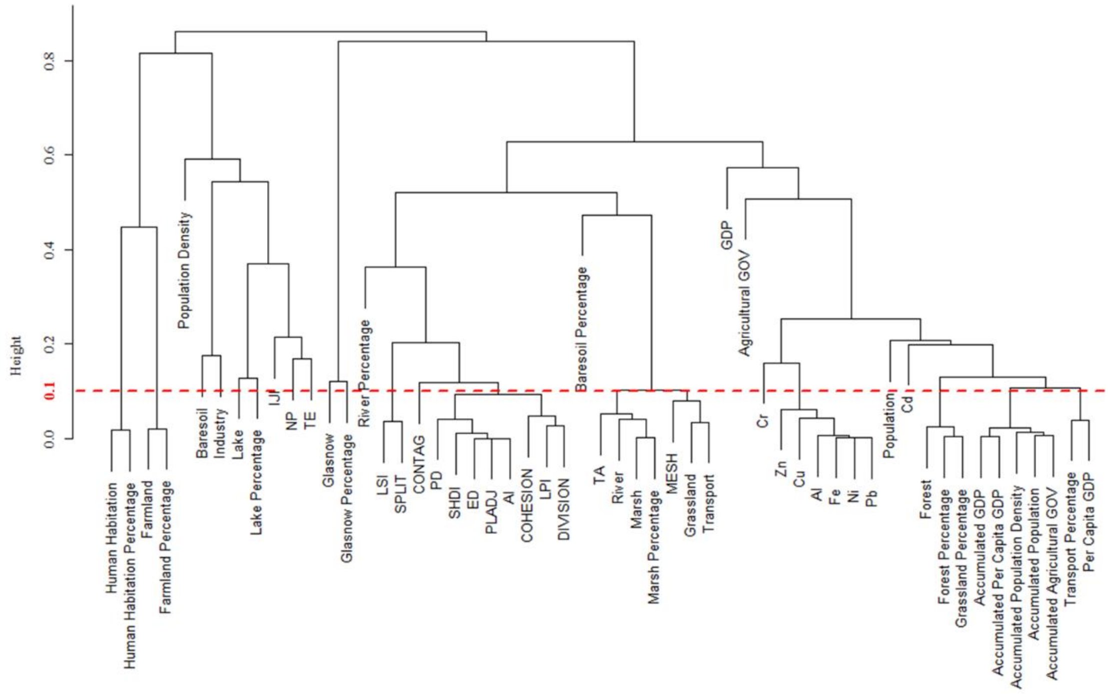

Fig. 10. HCA dendrogram based on the measured by $1\text{-}r^2$.

Table 1. Area and proportion of each land cover type.

Land cover classes	Shiqu		Dege		Ganzi	
	Area(km^2)	Proportion (%)	Area(km^2)	Proportion (%)	Area(km^2)	Proportion (%)
Bare Soil	561.77	3.12%	398.24	6.18%	309.39	4.22%
Farm Land	4.81	0.03%	22.86	0.35%	80.18	1.09%
Forest	1.10	0.01%	644.45	10.00%	774.57	10.56%
Glacial and Snow	131.10	0.73%	286.03	4.44%	285.20	3.89%
Grassland	15428.98	85.68%	4997.31	77.57%	5793.54	78.96%
Human Habitation	1.45	0.01%	2.65	0.04%	7.66	0.10%
Industrial Land	0.45	0.00%	0.23	0.00%	0.19	0.00%
Lake	9.48	0.05%	5.18	0.08%	0.19	0.00%
Marsh Land	1693.74	9.41%	36.08	0.56%	23.84	0.32%
River	143.26	0.80%	38.94	0.60%	55.63	0.76%
Transportation Land	32.26	0.18%	10.68	0.17%	6.86	0.09%

Table 1 (Continuous). Area and proportion of each land cover type

Land cover classes	Xinlong		Litang		Yajiang	
	Area(km^2)	Proportion (%)	Area(km^2)	Proportion (%)	Area(km^2)	Proportion(%)
Bare Soil	451.32	5.64%	191.70	4.11%	363.59	4.80%
Farm Land	38.69	0.48%	15.72	0.34%	38.01	0.50%
Forest	3540.41	44.22%	2274.36	48.78%	4868.50	64.29%
Glacial and Snow	330.76	4.13%	104.38	2.24%	81.37	1.07%
Grassland	3581.73	44.74%	2062.01	44.23%	2181.47	28.81%
Human Habitation	1.00	0.01%	0.00	0.00%	0.98	0.01%
Industrial Land	0.37	0.00%	0.00	0.00%	0.11	0.00%
Lake	13.62	0.17%	0.00	0.00%	1.02	0.01%
Marsh Land	5.77	0.07%	0.00	0.00%	0.00	0.00%
River	39.59	0.49%	14.16	0.30%	37.88	0.50%
Transportation Land	2.89	0.04%	0	0.00%	0	0.00%

Table 2. Landscape pattern indices of the study area.

Shiqu	**TA**	**NP**	**PD**	**LPI**	**TE**	**ED**	**LSI**	**CONTAG**
	1800824	22492	1.25	82.39	38454870	21.35	73.64	85.28
	PLADJ	**IJI**	**COHESION**	**DIVISION**	**MESH**	**SPLIT**	**SHDI**	**AI**
	96.75	36.98	99.96	0.32	1223736.26	1.47	0.56	96.79
Dege	**TA**	**NP**	**PD**	**LPI**	**TE**	**ED**	**LSI**	**CONTAG**
	644263	17027	2.64	71.40	24016890	37.28	76.85	77.48
	PLADJ	**IJI**	**COHESION**	**DIVISION**	**MESH**	**SPLIT**	**SHDI**	**AI**
	94.33	41.11	99.91	0.49	328937.41	1.96	0.84	94.40
Ganzi	**TA**	**NP**	**PD**	**LPI**	**TE**	**ED**	**LSI**	**CONTAG**
	733726	19702	2.69	62.68	25446540	34.68	77.08	78.44
	PLADJ	**IJI**	**COHESION**	**DIVISION**	**MESH**	**SPLIT**	**SHDI**	**AI**
	94.70	42.94	99.89	0.59	298410.58	2.46	0.80	94.76
Xinglong	**TA**	**NP**	**PD**	**LPI**	**TE**	**ED**	**LSI**	**CONTAG**
	800609	32222	4.02	21.15	42916860	53.61	121.78	70.40
	PLADJ	**IJI**	**COHESION**	**DIVISION**	**MESH**	**SPLIT**	**SHDI**	**AI**
	91.90	35.34	99.81	0.90	79176.66	10.11	1.09	91.96
Litang	**TA**	**NP**	**PD**	**LPI**	**TE**	**ED**	**LSI**	**CONTAG**
	466235	16748	3.59	31.13	21566220	46.26	82.39	65.07
	PLADJ	**IJI**	**COHESION**	**DIVISION**	**MESH**	**SPLIT**	**SHDI**	**AI**
	92.91	46.34	99.77	0.85	69570.70	6.70	0.96	92.98
Yajiang	**TA**	**NP**	**PD**	**LPI**	**TE**	**ED**	**LSI**	**CONTAG**
	757294	24862	3.28	58.83	28723440	37.93	85.03	73.96
	PLADJ	**IJI**	**COHESION**	**DIVISION**	**MESH**	**SPLIT**	**SHDI**	**AI**
	94.22	37.34	99.89	0.64	270170.13	2.80	0.89	94.28

Table 3. The HCA clusters with r^2 greater than 0.9

No.	Clusters of Indices
1	Al, Fe, Ni, Cu, Zn, Pb
2	TA, Marsh Land, Marsh Land Percentage, River
3	PD, LPI, ED, PLADJ, COHESION, DIVISION, SHDI, AI
4	LSI, SPLIT
5	MESH, Grassland, Transportation Land
6	Farm Land, Farm Land Percentage
7	Forest, Forest Percentage, Grassland Percentage
8	Human Habitation, Human Habitation Percentage
9	Transportation Land Percentage, Per Capita GDP
10	Accumulated Population, Accumulated Population Density, Accumulated GDP, Accumulated Per Capita GDP, Accumulated Gross Output Value of Agriculture

Table 4. Stepwise regression models of heavy metal elements, landscape pattern and economic indices

Indices	Regression models	R^2	F	*Sig.*
Al	Al = -64.629 + 0.039APCGDP	0.875	195.26	0.00
Fe	Fe = 36.489 + 0.072APCGDP – 6941.699HumanhabP	0.875	102.174	0.00
Ni	Ni = 0.707 + 0.000138 APCGDP – 15.078 HumanhabP	0.863	85.086	0.00
Cu	Cu = 1.238 + 0.083ForestP	0.776	97.105	0.00
Zn	Zn = 11.841 + 0.212 ForestP – 40.671TransportP	0.907	132.296	0.00
Pb	Pb = 0.4 + 0.155ForestP – 0.001Forest	0.873	92.864	0.00
TA	TA = 545952.613 + 2674.105Marsh – 438341.759MarshP + 5935.679River	0.985	586.115	0.00
MESH	$MESH$ = 42505.135 + 34904.903Transport	0.922	329.144	0.00
TransportP	$TransportP$ = 0.328 – 2.22×10^{-5}PCGDP	0.961	695.189	0.00

R^2, the coefficient of determination; APCGDP, accumulated per capita GDP; HumanhabP, human habitation percentage; ForestP, forest percentage; TransportP, transportation land percentage; Forest, area of forest; Marsh, area of marsh land; MarshP, marsh land percentage; River, area of river; Transport, area of transportation land; TransportP, transportation land percentage; PCGDP, per capita GDP.