STUDY ON ECOLOGICAL RISK ASSESSMENT OF DIFFERENT LAND USE TYPES BASED ON HMER MODEL – TAKING THE DAXIA RIVER IN GANSU, CHINA AS AN EXAMPLE

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(Received 10th Jun 2019; accepted 28th Aug 2019)

Abstract. The effective heavy metal content of soil indicates ecological environmental risks. The study takes the typical watershed area in northwestern China as a research area. The real-time and rapid risk assessment of ecological environment can be achieved through the monitoring value of normalized difference vegetation index (NDVI) of remote sensing information and environmental factors, and a heavy metal ecological risk assessment model (HMER) for the evaluation of the watershed is built. The research results show that the change of the effective heavy metal content in different areas of the watershed is affected to some extent by the influence of geographical location and human activities. Among them NDVI and the content of heavy metals, precipitation and temperature, and a nonlinear relationship between the average heavy metal content and the ecological risk index HRI. The establishment of HMER research model is applied to different land use types to evaluate the ecological risk level of the watershed, explore the ecological risk level of different land use types in the same region, and in different regions. The results of the study emphasize that the risk assessment of the watershed can be carried out through remote sensing information and environmental factors.

Keywords: *soil, heavy metals, HMER, land use type, NDVI*

Introduction

Soil safety is closely related to agricultural production, food safety, human health and ecological health (Shi et al., 2019). At present, about 20% of China's land ecological environment is under high risk, with a total area of about 0.11 billion km² (Liu and Zhang, 2010). Among them, the effective pollution status of heavy metals in soil environment has received increasing attention (Yang et al., 2018). Studies have shown that heavy metals pose a high risk of environmental exposure by spreading and accumulating between plants (the main pathways includes crops and vegetables) and animals (Sawut et al., 2018). The heavy metal environmental hazard released by the ecological chain link process has a negative impact on the viability of urban trees (Yu et al., 2018). Frequent human activities accelerate the release of heavy metal activity, causing heavy metals in the soil to pose a public health threat (Doabi et al., 2018).

In different land use types, soil moisture content will change (Tang et al., 2018). Physical properties such as soil texture, porosity, structure, and chemical properties such as absorption and cushioning are also different (Liang et al., 2018). As the content of heavy metals in soil is related to these properties of soil, there are differences in the distribution and quantity accumulation of heavy metals in soil of different land use types (Su et al., 2013), which leads to the phenomenon that the content of heavy metals in soil of different land types is different (Wang et al., 2016). Some scholars have carried out ecological assessment studies on the production of heavy metals in different

land use types in the same area (Zhou et al., 2017). Some scholars have used different evaluation methods to study the status of heavy metal pollution (Liu et al., 2013). The reasons for these differences and the relationship between soil physical and chemical properties and heavy metals under different land use types need further verification (Wu et al., 2018). Traditional evaluation methods all require field sampling, but due to the weather, geographical location and other factors, the difficulty of sampling is increased, and the sample processing time is also relatively long. These factors cause great obstacles to further study and understanding of regional heavy metal ecological risk.

This paper studies the impact of human activities on environmental and ecological risks from the perspective of land use types and the correlation between climatic and environmental factors and heavy metals. The precipitation, temperature and NDVI of the study area are analyzed. The extraction and comparison of different land use types were carried out, and then the remote sensing data and environmental data and the ecological assessment model of the average content of heavy metals were established in the soil over a long period of time. The relationship between different land use types and ecological risk index was explored, and then the remote sensing data was used to estimate the distribution of heavy metals in the basin and construct an ecological risk assessment model. The research methods are applied to different land use types in the same area and the same land use types in different areas to determine their ecological risk levels. Because of the difficulty of sampling different land use types in the basin area, it is more accurate to carry out ecological risk assessment for the study basin area. The research results provide a theoretical reference for the assessment of soil heavy metal ecological risk in small and medium watersheds, the prevention and treatment of heavy metals in farmland and the methods of restoration.

Materials and methods

Research area overview

The research area is the Daxia River which flows through the southwestern part of Gansu Province in China. The study area is located between 102°02'~103°23' East longitudes and 34°51'~35°48' North latitude. There are two river sources in the Daxia River, namely Xiahe and Luohe (Yang, 2013). The Daxia River originates in the southern part of Tongren County and the west of Xiahe County in Qinghai Province, and flows through Qingshui Gorge in Xiahe County, passes through Tumen Gate and enters Maji Town of Linxia County, and passes through Yinji and Xinji Towns into Linxia City. From the estuary, the river enters the Liujiaxia Reservoir and merges into the Yellow River. It is called “the first-level tributary of the upper reaches of the Yellow River” (Wang, 2016). According to the water conservancy department in Linxia Prefecture, 45.5% of the river water resources in the area are affected by different levels of anthropogenic pollution, and 11.6% has water quality that is lower than the drinking standard. More than 90% of municipal water resources are threatened by water security (Chen, 2015). In terms of the geographical distribution of water pollution, the water quality of the main stream is higher than in the tributaries, and the upstream water quality is better than the downstream. A major source of water pollution is the mines (Luo, 2017). Water conservation in the Daxia River Basin is regarded as an important foundation for the sustainable social and economic development in the ethnic minority areas (Lin, 2015).

Source and processing of remote sensing data

Remote-sensing data are mainly provided by the Geospatial Data Cloud (<http://www.gscloud.cn/>) and the Landsat 8 OLI_Thermal Infrared Sensor (TIRS) remote sensing satellite data from the LANDSAT series of data provided by the United States Geological Survey (USGS) (<https://earthexplorer.usgs.gov/>). The applied remote sensing image is in the period from 2015 (January to December) to 2017 (January to December), and its spatial resolution is 30 m × 30 m. The ENVI software was used to calculate the corresponding NDVI values for radiometric calibration, image mosaic, image cropping, and atmospheric correction on the smoke image of the study area, and to remove the outliers and center standardization. The NDVI is defined as the ratio of the difference between near-infrared (NIR) and visible-red-red (R) bands and the sum of the two bands, $NDVI = (NIR - R) / (NIR + R)$. In vegetation remote sensing, NDVI is the most widely used, as (1) NDVI can be applied to detect vegetation growth status, vegetation coverage, and to eliminate some radiation errors; (2) negative values indicate that the ground cover is cloud, water, snow, etc., with a high reflection for visible light; 0 means rock or bare soil, where NIR and R is approximately equal; positive values indicate vegetation coverage, and the positive value increases with increasing coverage (Yuan and Gu, 2018). The average monthly NDVI of the study area from 2015 (January to December) to 2017 (January to December) is shown in *Figure 1*.

Figure 1. NDVI monthly average

Source and treatment of heavy metal data

In order to determine the number of samples more reasonably, this paper uses the Cochran method to estimate the optimal number of samples and sampling points for the construction constructed with pure random sampling of the study area. And there are 114 sampling points, including 24 fixed sampling points and 90 random sampling points. Among them, the fixed sampling point refers to the point to be collected every time, and the random sampling point is the point that is not necessarily collected every month, which can make the sample closer to the real situation. The main sampling time for this study is 2015 (January to December) to 2017 (January to December). Among them, the sample collection is performed once a month. The distribution of sampling points is shown in *Figure 2*. When collecting samples, a hand-held GPS device was used, and a plastic spoon was used to take 0-20 cm of the upper layer of the bottom

mud. The soil sample was dried and ground, after passing through a 200-mesh nylon sieve. In addition, the sample was processed by microwave digestion. Finally, the content of heavy metals was determined by inductively coupled plasma optical emission spectrometer (ICP-OES). By combining remote sensing images and combining field visits to study areas, we learn about the main sources of heavy metals in the study area, such as plant emissions, and the use of pesticides.

Figure 2. Study area sampling point map

Source and treatment of precipitation and temperature

Surface meteorological data from the China Meteorological Data Network (<http://data.cma.cn/site/index.html>) is typically used as the main source of precipitation and temperature data. Monthly average temperature and monthly average precipitation data from January 2015 to December 2017 was obtained for the study.

Results and discussion

Relationship between regional factors

Impact of climatic factors on NDVI

As the seasons change, the value of NDVI will change due to variations in moisture and temperature (Wang et al., 2018). Changes in vegetation cover are also affected by the combined or synergistic effects of hydrological conditions (such as temperature, precipitation, and humidity) (Liu et al., 2018). Due to little variation in pH and land use type in the study area, this paper focuses on the differences in precipitation and temperature. The amount of precipitation, temperature, and NDVI is affected to some extent by human activities. The monthly average NDVI values from January 2015 to December 2017, the monthly average precipitation and the monthly average temperature were used for correlation analysis.

It can be observed that the correlation between monthly average NDVI value and monthly average precipitation is 0.807, and the correlation between monthly average NDVI value and monthly mean temperature is 0.808. The relationship between temperature and NDVI ($P = 0.01 < 0.05$), and precipitation and NDVI ($P = 0.02 < 0.05$) are statistically significant. Details are shown in *Figure 3a, b*.

Figure 3. Relationship between NDVI and precipitation temperature

Influence of climatic factors on heavy metal content

Field measurements showed evidence of the presence of Cd, Cr, Cu, Pb, and as in the research area. The content of heavy metals is related to the migration of heavy metals. The speed of migration is linked to precipitation and temperature, and the cumulative effect of heavy metals in organisms is related to climatic factors (Ahonen et al., 2018). The soil heavy metal content is significantly correlated with the annual average precipitation and temperature at the sampling point (Zhou et al., 2018). Human activities indirectly affect the content of heavy metals by affecting climate change. The monthly average heavy metal content of the five elements was calculated, and a correlation analysis was undertaken for monthly precipitation and monthly average temperature. The correlation between monthly heavy metal content and precipitation was -0.79, and the correlation between monthly heavy metal content and temperature was -0.784, and the significance was sig. = 0.03, sig. = 0.02, respectively. The average heavy metal content in soil is negatively correlated with precipitation and temperature. Erosion and rainfall runoff will reduce the content of heavy metals (Li et al., 2011). An increase in temperature causes increased acidity and an increase in the activity of heavy metal ions, which means that the heavy metal content increases. However, the increase of heavy metal active ions means that the water solubility of heavy metal ions increases. Thus, heavy metal content can be seasonal, increasing with an increase in temperatures. The scouring effect is notable, and will reduce the heavy metal content of the soil. Details are shown in *Figure 4a, b*.

Ecological risk assessment model

Remote sensing data prediction of heavy metal average content model

The heavy metal content, the average monthly NDVI, the monthly average precipitation, and the monthly average temperature data from 2015 (January to December) to 2017 (January to December) in the Daxia River Basin were modeled using SPSS20 statistical software. The modeling result was $R^2 = 0.866$.

$$H = -0.002P - 54.2876N - 0.042T + 34.443 \quad (\text{Eq.1})$$

where H is the average heavy metal content, P and T are the precipitation amount and temperature, respectively; N is the NDVI value.

Figure 4. Relationship between monthly heavy metal content and water purification temperature

From 2015 (January to December) to 2017 (January to December), the fixed sampling points of the study area and the values of the random sampling points are measured. After treatment, the content of heavy metals was determined by inductively coupled plasma optical emission spectrometer (ICP-OES), and then the values were averaged. The comparison with the average heavy metal content of the soil predicted by *Equation 1* is as follows. *Equation 1* can be used to predict the average heavy metal content of the study area. From *Figure 5*, the average heavy metal content in August is the lowest. The vegetation in August is the lushest, and the vegetation has an inhibitory effect on the dissolution of heavy metal content in the soil.

Figure 5. Comparison of measured and calculated values of monthly heavy metal content

Establishment of ecological risk assessment model

The Hakanson Ecological Risk Index is a commonly used potential ecological risk assessment index for heavy metals (Hakanson, 1980) which predicts the slow release processes and potential effects of heavy metals in the soil. In response to this potential hazard, the Swedish environmentalist Lars Hakanson introduced the potential ecological risk index (HRI) in 1980.

$$HRI = \sum_{i=1}^n E_r^i = \sum_{i=1}^n T_r^i \cdot C_r^i = \sum_{i=1}^n T_r^i \cdot \frac{C_f^i}{C_z^i} \quad (\text{Eq.2})$$

where: HRI is the potential ecological risk index of n kinds of heavy metals in the sample. E_r^i is the single potential ecological risk index of the sample heavy metal I ; T_r^i is the toxicity response coefficient of the T heavy metal I ; C_r^i is the pollution coefficient of the heavy metal I ; C_f^i is the measured value of the heavy metal i in the sample, and C_z^i is the specific gravity metal value of the uncontaminated sediment before industrialization. (This can also be replaced by the local sediment background value.) The geochemical background values of the heavy metals in the study area (Wang and Lian, 1993) are shown in *Table 1*, and the classification criteria for the potential ecological hazard index of heavy metals (Li et al., 2015) are shown in *Table 2*.

The size of HRI value is related to the content of heavy metal. Therefore, the average heavy metal content H calculated in *Equation 1* is the independent variable, and the HRI calculated by *Equation 2* is the dependent variable, and the linear fitting is performed. The fitting result is shown in *Table 3*.

Table 1. Geochemical background values of soil heavy metals in the study area (Wang and Lian, 1993)

Project	Copper	Lead	Arsenic	Cadmium	Chromium
Background values	28.91	20.83	14.03	0.130	75.35

Table 2. Classification criteria for potential ecological hazard index of heavy metals (Li et al., 2015)

Risk level	E_r^i	HRI	Potential ecological risk
A	≤ 40	≤ 150	Low
B	40~80	150~300	Medium
C	80~160	300~600	Slightly serious
D	160~320	600~1200	Serious
E	> 320	> 1200	Extremely serious

E_r^i is the potential ecological hazard index of heavy metals I; *HRI* is the potential ecological risk index

Table 3. Fitting results of HRI and average heavy metal content

Model type	Linear function	Logarithmic function	Countdown function	Quadratic function	Cubic function	Composite function	Power function
Correlation	0.731	0.682	0.629	0.88	0.893	0.825	0.785

By comparing the fitting results, the cubic function fitting is ideal, the cubic formula is selected, and the specific fitting *Equation 3* is the remote heavy metal ecological risk assessment model (HMER) follows:

$$HMER = 0.02H^3 - 0.718H^2 + 228.034 \quad (\text{Eq.3})$$

where H represents the average heavy metal content calculated in *Equation 1*; HMER represents the ecological risk assessment value, and its classification is referred to *Table 2*.

Using the data from 2018 (January to June) for verification, a comparison between the verification result and the sampling result is shown in *Figure 6* (Numbers 1-12 and Numbers 13 to 19 are the data of the sample area and verification area, respectively). The relationship between the watershed heavy metal ecological risk index, RRI, and the meteorological remote sensing information can be expressed by *Equation 3*.

Model application

Application of different land use type models in the same area

Due to the relatively large difficulty of different land use types in the whole study area, this method is used to evaluate the ecological risks of different land use types.

By using ENVI software to read, inlay, trim, and atmospheric correction of remote sensing images with less cloud cover, the unsupervised classification K-Means and the combination of on-site surveys are used to classify the land as shown in *Figure 7*. The map is processed by Majority/Minority analysis, and the clustering process is carried out to ensure the continuity of the space. The filtering problem is also used to solve the island problem in the picture, so the image is close to the real situation. In this study, land types are mainly divided into water area, grassland, town, cultivated land and woodland, as shown in *Figure 7*. Among them, the NDVI value is usually in the range

of $[-1, 1]$. The negative value of the waters is normal. When the waters are extracted, the water bodies may have positive values because some vegetation grows in the water and floats on the water surface. Similarly, when extracting land use types such as grassland, woodland, cultivated land, and towns, it may be affected by the background of the plant canopy, such as soil, wet ground, snow, dead leaves, roughness, etc., and will get negative values. NDVI values of each land use type were calculated by using mask and other operations, as shown in *Table 4*.

Figure 6. Comparison of the HMER model and the Hakanson model

Figure 7. Daxiahe land use type classification map

Table 4. NDVI values for different land use types

Types	Min	Max	Stdev	Total
Waters	-0.76625	0.59237	0.104546	7014712
Grassland	-0.4982	0.62051	0.198214	10064524
Town	-0.74373	0.600615	0.126054	8560026
farmland	-0.72819	0.624793	0.130765	542308
woodland	-0.70428	0.606539	0.362047	729353

According to *Equation 1*, the different land use types of average NDVI value of the heavy metal content in the research area, precipitation, temperature factors, in order to compare the influence of different land use types on heavy metal content, the average rainfall and temperature in different areas of the process, to get the precipitation and temperature in the whole area. The corresponding NDVI value, precipitation and temperature, etc. were substituted into the corresponding formula. The results are shown in *Table 5*.

Table 5. Ecological risk levels of different land use types in the Daxia River Basin

Types	HMER	Risk level	Potential ecological risk index
Waters	-21.5568	A	Low
Grassland	113.5366	A	Low
Town	168.7537	B	Medium
Farmland	144.7092	A	Low
Woodland	69.37197	A	Low

It can be seen from *Table 5* that the waters are negative and do not participate in the discussion. The potential risk index of grassland, farmland and forest land is low pollution, and the HMER index of woodland is the lowest. It can be inferred that the planting of woodland in this study area can help inhibit the heavy metals and reduce the ecological risk. The ecological risk level of the town is medium. Due to the large urban population, human activities are frequent. It can be seen that the impact of human activities on soil heavy metal content is positive, so the ecological risk level of towns is high.

Application of different land use types in different regions

Read, mosaic, crop, and atmospheric correction of remote sensing images with less cloud content by using ENVI software. The land is classified using unsupervised classification K-Means and combined with on-site surveys. Then, using mask technology, according to the administrative boundaries of each small area, it is divided and the NDVI value is calculated, as shown in *Figure 8* and use the average of the precipitation in each area from 2015 to 2017 and the temperature average to be substituted into *Equations 1* and *3*, as shown in *Table 6*.

It can be seen from *Table 6* that the ecological risk pollution levels of different land use types in small areas are low or medium, among which the ecological risk levels of grassland, farmland and forest land in Dongxiang County, Linxia City, Llinxia County,

Hezuo City, Xiahe county, Hezheng county, Xunhua Salar Autonomous County and Tongren County are all low. The ecological risk levels of Dongxiang County, Linxia City, Linxia County, Hezuo city, Xiahe County, Hezheng County and Xunhua Salar Autonomous County were all medium, while the ecological risk levels of Tongren County were low.

Figure 8. Small area land use type

Table 6. Ecological risk levels of different land use types in small areas

Region	Grass		Towns		Farmland		Woodland		Waters
	P-I	P-L	P-I	P-L	P-I	P-L	P-I	P-L	
Dongxiang County	85.365	A-L	243.455	B-M	143.4	A-L	70.365	A-L	No
Linxia City	83.215	A-L	270.532	B-M	148.653	A-L	68.447	A-L	No
Linxia County	97.117	A-L	184.663	B-M	146.637	A-L	72.256	A-L	No
Hezuo City	132.419	A-L	168.321	B-M	84.571	A-L	40.752	A-L	No
Xiahe County	140.327	A-L	179.988	B-M	79.634	A-L	56.766	A-L	No
Hezheng County	63.021	A-L	193.365	B-M	139.521	A-L	86.329	A-L	No
Xunhua Salar Autonomous County	86.130	A-L	153.654	B-M	136.774	A-L	12.114	A-L	No
Tongren County	74.557	A-L	68.776	A-L	66.521	A-L	38.123	A-L	No

A-L: A-low; B-M: B-medium; P-I: pollution index; P-L: pollution level

Combined with the remote sensing image map (Fig. 5) and the local interview survey, we can see that there are many towns in Dongxiang county, Linxia city and Linxia county. Human activities (factory emissions, transportation, etc.) cause high ecological risk assessment, and the ecological risk pollution index is close to 150 (close to c-heavy). Therefore, Dongxiang County, Linxia City and Linxia County can increase the planting of forest land to alleviate the ecological risk of this area.

Conclusion

From Jan 2015 to Dec 2017, the NDVI of the study area increased, in areas where humans live in more areas, the NDVI value is lower. The NDVI is significantly affected by precipitation and temperature. The correlation coefficient between precipitation and NDVI is 0.807, and the correlation coefficient between temperature and NDVI is 0.808. It can be seen that the temperature has a greater influence on the NDVI. The heavy metal content was negatively correlated with temperature and precipitation, and the correlation coefficients were -0.79 and -0.784, respectively.

The ecological risk level of land use types in grassland, cultivated land and forest land in the Daxia River Basin is low. The town is medium. The overall ecological risk is better. The ecological risk pollution levels of different land use types in small areas are also low or medium, including the grasslands of Dongxiang County, Linxia City, Linxia County, HeZuo City, Xiahe County, Hezheng County, Xunhua Salar Autonomous County and Tongren County. The ecological risk grades of cultivated land and forest land are all low. The land use types are Dongxiang County, Linxia City, Linxia County, Hezuo City, Xiahe County, Hezheng County, Xunhua Salar Autonomous County, and the ecological risk level of Tongren County is low. The towns of Dongxiang County, Linxia City and Linxia County are more distributed, and their ecological risk pollution index is close to heavy pollution. Therefore, Dongxiang County, Linxia City and Linxia County can increase the planting of forest land to alleviate the ecological risk of the area. This paper establishes remote sensing data and average heavy metal content model in the Daxia River Basin. The ecological risk assessment HMER model and method, through data verification shows that the model has potential application value and certain degree of implementation. It laid the foundation for the subsequent heavy metal pollution of the soil in the study area.

The model under study has an intentional significance for the risk assessment of the Daxia River Basin. Whether the HMER model has a more accurate assessment effect on the basin area of other vegetation and industrial types remains to be studied by the researchers. The follow-up work of this paper is mainly to study the data monitoring through data sensors and establish intelligent data detection and analysis in order to increase the efficiency of the relevant staff.

Acknowledgments. This work was supported by the National Natural Science Foundation of China under Grant No.61563047.

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