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Establishment of an integrated decision-making method for planning the ecological restoration of terrestrial ecosystems

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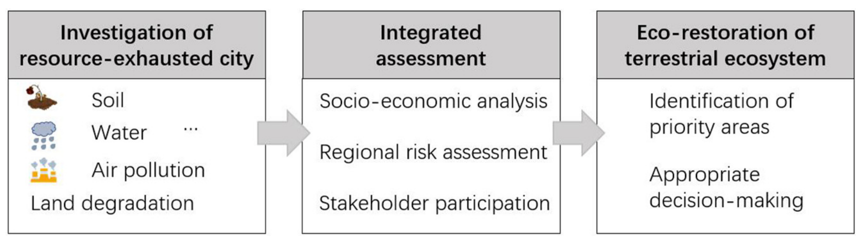
HIGHLIGHTS

- Integrated assessment used in study of ecological restoration was the first attempt.
- RRA expanded the methods for ecological restoration of terrestrial ecosystems.
- Multi-factor investigation enabled comprehensive restoration of terrestrial ecosystem.
- Nonlinear model reduced the uncertainty of risk calculation.
- MCDA methods reflected practical limits of restoring the terrestrial environment.

GRAPHICAL ABSTRACT



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ABSTRACT

Ecological restoration of terrestrial ecosystems facilitates environmental protection and enhances sustainable development of land resources. With increasingly severe land degradation, new and effective methods must be developed for the restoration of ecological functions. In this study, we developed a regional risk assessment approach to support the planning of ecological restoration of a terrestrial ecosystem located in the Daye area in central China. The study area was divided into six sub-regions where ecological risks were characterized by building a non-linear model to represent ecological interactions among the risk components there. Socio-economic conditions in the areas were evaluated and presented using an analytic hierarchy process. Assessment of different stakeholders there was conducted based on multiple-criteria decision analysis. Then, integrated assessment was performed using the technique of order preference for an ideal solution. We divided the degraded land in Daye into areas with different priorities for restoration or rectification and presented corresponding sequential time intervals for the action. The results are as follows: (i) the top priority rectification areas (totaling 358 km^2) are mainly distributed in northeast and northwest regions; (ii) the high priority rectification areas are concentrated in the central region spanning 226 km^2; (iii) the medium priority rectification areas comprised a large amount of arable and forest land spanning 605 km^2; and (iv) the low priority rectification areas cover the rest part of the Daye area spanning 195 km^2. The assessment tool was proven to be useful in planning regional ecological restoration in terrestrial ecosystems.

Abbreviations: RRA, regional risk assessment; MCDA, multi-criteria decision analysis; TOPSIS, technique for order preference by similarity to ideal solution; AHP, analytic hierarchy process; GIS, geographic information systems; NPP, Net Primary Productivity; COD, chemical oxygen demand; NH3-N, ammonia–nitrogen; ERA, ecological risk assessment.

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1. Introduction

Land degradation is a process of decrease or loss in the ecological service functions of land due to interference in natural processes mainly by human activities (Turner et al., 2016; Liu et al., 2018a, 2018b; Huang et al., 2019; Guo et al., 2020). The degradation is also caused by habitat loss, soil erosion, environmental pollution and reduced production. It then leads to landscape damage and biodiversity decline, and ultimately threatens human health (Bai et al., 2014; Djuma et al., 2017; Chu et al., 2019) and hinders global and regional economic development (Bryan et al., 2018; Cowie et al., 2018). Therefore, restoration of land resources and the associated ecosystems is of great significance, and has been the primary focus of many environmental studies (Li et al., 2015; Cao et al., 2017; Mao et al., 2018). Ecological restoration is restore a spoiled ecosystem to its original state (Palmer and Filoso, 2009; Gao and Bryan, 2017; Hou et al., 2018a, 2018b). Thus, the restoration of a land ecosystem requires both ecological and socioeconomic knowledge to determine the causes and mechanisms involved in the degradation, and also requires exploring techniques and methods that can be used to restore and reconstruct the degraded ecosystem. The ultimate goal is to retain the service functions of the terrestrial ecosystem while enabling the society and the economy to develop in a sustainable manner.

Previous studies on the restoration of terrestrial ecosystems concerned the environment, economy, social culture, and infrastructures (Halme et al., 2013; Turner et al., 2016; Mao et al., 2018). Restoration of the environment includes remediating contaminated soil, treating contaminated water, preventing soil erosion and salinization of soil, and controlling land desertification (Ran et al., 2013; Jiang et al., 2014; Cheng et al., 2018; Hou et al., 2018c; Wang et al., 2019a, 2019b). Economic recovery calls for preservation of arable land, reclamation of industrial wasteland, encouragement of afforestation, and prevention of land impoverishment (Mu et al., 2013; Ma et al., 2014; Lei et al., 2016; Lu et al., 2018). Restoration of social culture requires maintenance of cultural landscapes, creation of proper habitats for biodiversity, and conversion of cropland to forest (Benayas et al., 2009; Adame et al., 2015; Rodriguez et al., 2015, 2016; Dawson et al., 2017). And improvement of infrastructures requires reconstruction of hazard-standing buildings, development of environment-friendly mining areas and coastal zones, construction of settlements for ecological refugees, urban parks and greenways, and exploitation of tourist land resources (Delang and Yuan, 2015; Sun et al., 2015; Wang et al., 2016; Yang et al., 2017), and so on.

However, previous assessment methods, suggestions for remediation, and analytical tools have proven to be inherently weak when applied to terrestrial ecosystem research. With respect to assessment methods used, mono-factor studies have been employed, and these cannot reflect the entire state of degradation of a terrestrial ecosystem and may not provide motivation for taking measures to comprehensively restore it (Yin and Yin, 2010; Yin et al., 2010; Guo et al., 2020). The restoration procedures used have not employed large-scale analysis, and this has resulted in a failure to identify ecological processes involved in land degradation, and has led to the blindness of the later restoration mechanism (Liu et al., 2007; Halme et al., 2013; Ren et al., 2015). In addition, recovery plans designed have not involved the participation of local stakeholders, which means that such plans are unlikely to gain public acceptance (Krueger et al., 2012; Luyet et al., 2012; Hou and Li, 2017). Researchers have often focused on the ecological reconstruction of the original landscape, but have failed to effectively reflect local environmental deterioration and human health risks. With respect to analytical tools, non-linear calculations (relating to the spatial heterogeneity and diversity of terrestrial ecosystems) need to be improved to reduce uncertainty in decision-making (Ren et al., 2015; Yang et al., 2008). Finally, processing and transforming different spatial data, such as quantitative or semi-quantitative (and even qualitative data) has not been achieved (Esmail and Geneletti, 2018; Souissi et al., 2019). Such issues can be solved by using a more powerful tool that uses a more scientific approach. In this study, therefore, we employ a regional risk assessment (RRA) approach together with multiple-criteria decision analysis (MCDA) techniques.

An RRA of a terrestrial ecosystem can be used to estimate possible ecosystem degradation risks caused by human activities and natural factors (Guo et al., 2017; Hou et al., 2017; Kang et al., 2018). As a precondition of environmental decision-making, it provides important information that supports environmental protection, resource sustainability, and even regional economic activities (Pizzol et al., 2016; Furlan et al., 2018; Wang et al., 2019a, 2019b). The major advantages of this methodology are that it presents the close relationships between ecological processes and human production activities (Stelzenmüller et al., 2010; Sun et al., 2015; Gallego et al., 2019), and that it reveals the complex mechanisms in ecological degradation under a capable analysis paradigm. The paradigm encompasses multiple stressors, pathways, and effect endpoints (Xu et al., 2016; Yao et al., 2015; Guo et al., 2017). In addition, the probabilistic representations of risk outcomes are helpful in considering alternative management options (Maldonado et al., 2016; Gupta and Baker, 2019). They facilitate the organization and processing of data to support local environmental administrators in policy making (Agostini et al., 2012; Zhao and Liu, 2016; Souissi et al., 2019), and they extend the use of large-scale ecological decision-making tools (Xu et al., 2015; Partl et al., 2017; Li et al., 2018).

Multi-criteria decision analysis (MCDA) helps to select the optimal decision from a series of alternative schemes based on some irrelevant and inconsistent rules and is thus an effective method of knowledge synthesis to support decision-making (Malczewski, 2004; Huang et al., 2011; Marttunen et al., 2017). This approach is used to provide a framework for integrating multiple opinions and evaluation criteria and to assign weights to them according to their importance before selecting the most suitable courses of action (Esmail and Geneletti, 2018; Watrobski et al., 2019). For current studies on land degradation, the advantages of MCDA are that it emphasizes the participation of different stakeholders, incorporates expert opinion, and that it enables multi-type data to be processed and combined in various algorithms to make accurate calculations (Dell'Ovo et al., 2018; Ristic et al., 2018) (Mallick et al., 2018; Schaefer and Thinh, 2019). In particular, this method combines geographic information systems (GIS) into one-dimensional values, taking into consideration of experts' preferences, to achieve a particular goal, and this helps considerable progress to be made in utilizing spatial data on a regional scale (Malczewski and Rinner, 2015; Souissi et al., 2019) (Qin, 2013; Rodríguez-Merinoa et al., 2020). The integrated application of RRA and MCDA can further promote the use of ecological models for spatial decision-making in various ecosystems, which involve database construction, spatial visualization simulation, collaborative analysis of regional resources and environment, and support models for decision making. The RRA-MCDA would be helpful in making spatial decision to dealing with the issue of land degradation in the studies area.

This study employed the RRA and MCDA as decision-making tools to support the ecological restoration of a terrestrial ecosystem in the traditional mining city of Daye, China. To this end, ecological risk, socioeconomic, and stakeholder assessments were conducted, and integrated analysis of the ecological restoration of the terrestrial ecosystem was performed. Priority areas for the regional ecological restoration of degraded land were then identified, and appropriate decision-making options for stakeholders in land management were designed.

2. Materials and methods

2.1. Study area and data source

2.1.1. Description of the study area

The City of Daye is located near the Yangtze River in southeast Hubei Province, Central China (114° 31′-115° 20′ E, 29° 40′-30° 15′ N) (Fig. 1), and the entire study area spans 1566.3 km^2. The area is rich in mineral deposits and has well-developed mining and metallurgy industries. There are 273 identified mineral deposits of varying sizes and types, 53 kinds of metal deposits and non-metallic minerals. The area is one of the nation's six copper production bases as well as one of 10 key large iron ore and building material production bases. The industrialization has increased significantly and the ecosystem of the entire area has suffered, which has led to dysfunctional ecosystem services and has resulted in soil contamination, water pollution, and the loss of arable land. The ecosystem in and around the city is varied and comprises lakes, rivers, forests, mines, arable land, gardens, and urban and rural residential areas. Daye City is representative of a resource-exhausted city, and ecological security is currently focusing on remediating degraded ecosystems on a regional scale. To ensure that accurate decisions are made to enable ecological restoration of the terrestrial ecosystem while incorporating a regional risk perspective, the study area was divided into six sub-regions based on economic, ecological, and geographical features (Chen et al., 2012; Li et al., 2014; Guo et al., 2017). The boundaries of the sub-regions were defined based on administrative divisions (Fig. 1).

2.1.2. Data source

The research team and the Daye City Land Resources Bureau conducted frequent investigations into the damage caused to the ecological environment by mining in Daye between 2014 and 2018. The investigation sites included a copper mine, an iron mine, coal mine, gold and silver mines, and other mine types, in addition to related smelting sites, ore dressing sites, quarries, tailing reservoirs, coal gangue dumps, and open metal mines. Over 800 problems relating to damage to the ground's surface and vegetation were identified, 349 geological hazards were identified (such as collapse, mine goaf, excavation, landslide, and water depletion), 550 instances of land damage caused by solid waste dumping were noted, and 1294 land plaques were determined (covering a total area of 6943.58 ha). With respect to the actual damage in each plot, our research group conducted a field investigation, plotting, took photographs, and conducted experimental analyses. During this period, the study team cooperated with the Daye Land Resources Bureau, Environmental Protection Agency, Wuhan University, Huazhong Agricultural University, and Hubei Normal University to organize expert groups that could assess the damage caused to the land ecological environment by mining. Of these, our expert group conducted an intra-industry interpretation, on-site verifications, and hazard level classification. Finally, our research team conducted spatial processing based on statistical information relating to each plot.

Based on interviews and a survey conducted by the Daye Environmental Protection Bureau, our research group obtained quarterly water quality monitoring data from 2016 to 2018 from water bodies at 37 sample monitoring points, including main rivers, lakes, and sensitive waters. We selected chemical oxygen demand (COD), ammonia–nitrogen (NH3-N), and heavy metal pollution as criteria to determine water quality deterioration. The group then conducted GIS spatial processing based on geographical information obtained from sampling points (Fig. 2).

Field soils were sampled in 2016, and a total of 225 valid samples were taken throughout the study area. The samples were representative of rural settlements, farmland, benchland, and irrigation districts throughout the surrounding industrial and mining areas, which are the main land use types in Daye City. They also represented the opinions on field investigation of the research group. Furthermore, soil tests were conducted to analyze the organic matter content, heavy metal content, acidity, water content, and surface thickness (Fig. 2).

Data obtained for the land use category were based on land use maps of Daye for 2014–2018. A large amount of data were obtained from the Daye Statistical Yearbook and from social surveys, such as data on population growth, land reclamation areas, the labor force, the application of pesticides and fertilizers, and the GDP, which reflects the strength of regions finances. Furthermore, information about the acid rain intensity was obtained from the Daye Environmental Protection Bureau, and that of natural disasters was collected from historical information about Daye (2000–2018). All the above processes were conducted using ArcGIS 10.2.

2.2. Framework for ecological restoration of the terrestrial ecosystem on a regional scale

Our research was initiated by the drive to transform resource-exhausted cities in China, which involves basic ecological restoration of degraded land (Zhu et al., 2016; Zhang et al., 2017, Zhang et al., 2018a, 2018b). The Yangtze River Basin is also a focus area for ecological and environmental protection (Kong et al., 2018; Qu et al., 2018; Ma et al., 2019). The study area in the present research was divided into six sub-regions based on their economic, ecological, and geographical features. Following

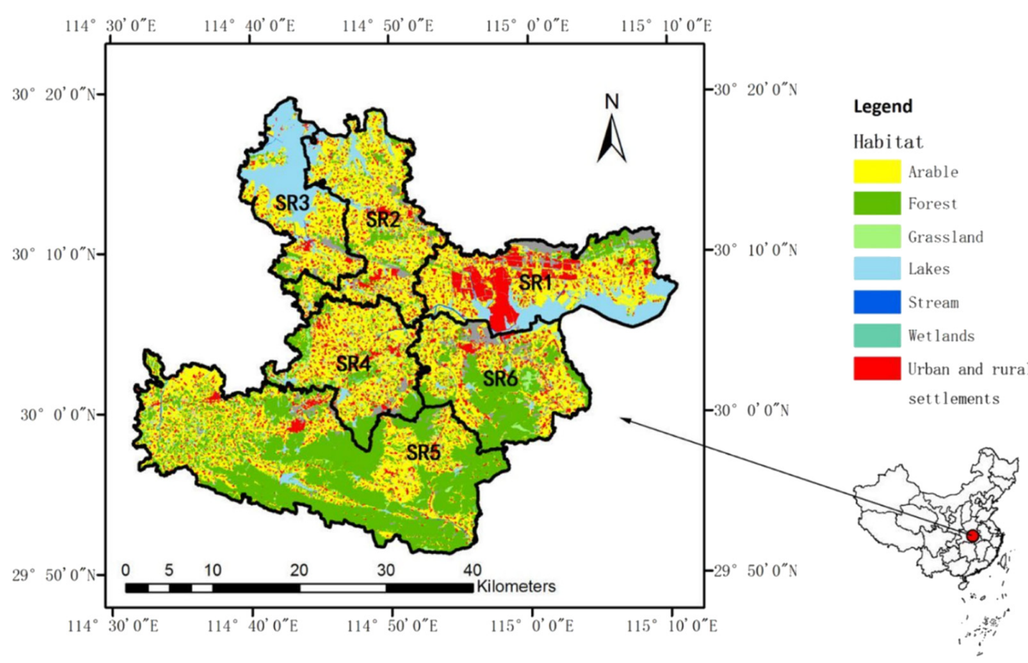

Fig. 1. Land use map of Daye City and its sub-regions.

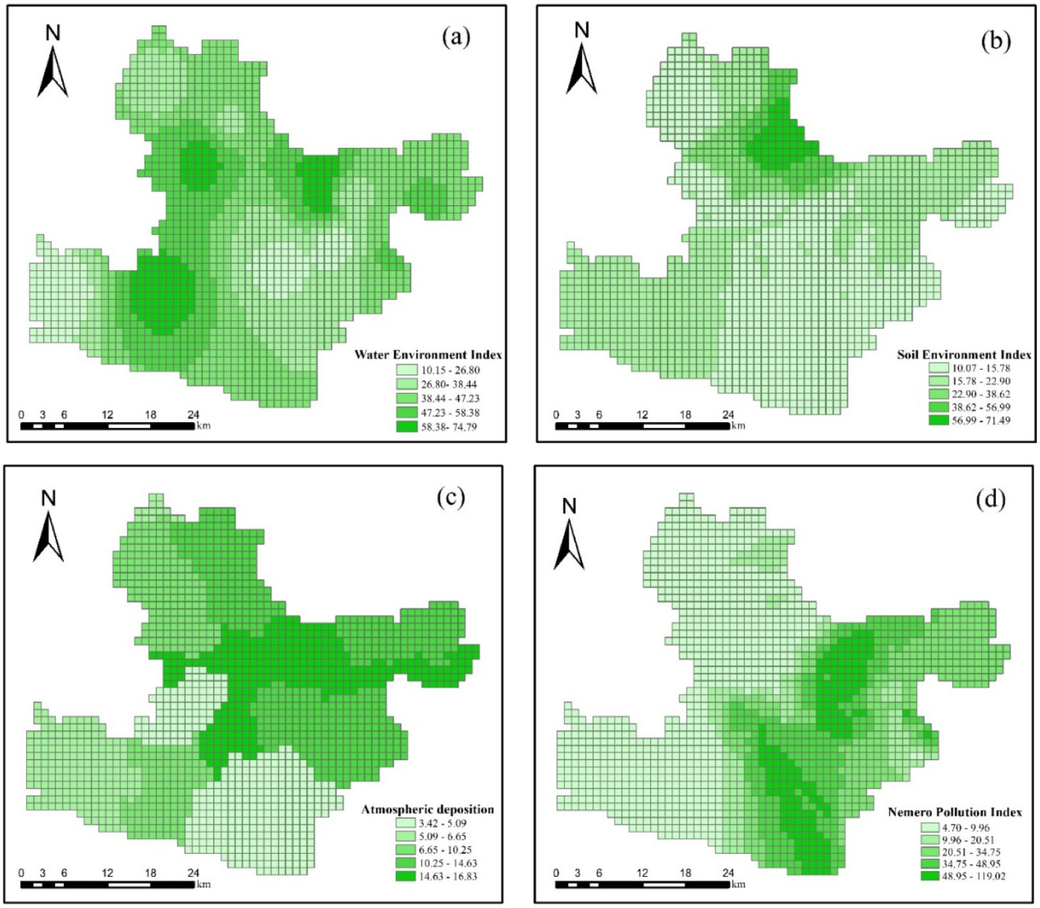

Fig. 2. The spatial distribution of observational variables of water quality environment, soil environment, atmospheric dust fall, and the Nemerow composite index of heavy metal in Daye area.

the concept of an ecological risk assessment (ERA), a hazard analysis and vulnerability analysis were conducted and an expose-response analysis for quantifying relationships. The regional ecological risk was then calculated using the nonlinear model designed in this research. The societal-economic status was evaluated using analytic hierarchy process (AHP) methodologies, and assessments of different stakeholders were conducted based on MCDA techniques. To combine the three analyses results of regional ecological risk, socio-economic status, and stakeholder values, we conducted an integrated assessment using the technique for order preference by similarity to ideal solution (TOPSIS) in ArcGIS 10.2. The procedures used in our approach are presented in Fig. 3.

2.3. Risk analysis

The proposed methodology used in the risk analysis of the resource-exhausted city of Daye was adapted from regional ecological risk assessment methodology that is widely used in ecological risk assessments of wetland, arid areas, islands, and animal husbandry cities (Fu and Xu, 2001; Shi et al., 2005; Wang et al., 2003). The following sub-sections provide a detailed description of the proposed methodology.

2.3.1. Model development

The regional ecological risk assessment methodology is generally based upon the following basic formula for measuring risk (Nath et al., 1996; Zabeo et al., 2011; Jin et al., 2019). Mathematically,

$$R = P \cdot D, \tag{1}$$

where R represents the ecological risk value; P represents the probability or intensity of occurrence; and D represents the potential possible damage, respectively. When focusing on the regional scale and spatial dimension, this formula can also be modified to include the integrated risk from multiple sources existing in different ecosystems (Hunsaker et al., 1989; Yin, 1995; USEPA, 1992; Landis, 2003). The integrated risk probability, P, and the potential ecological damage index, D, (which is also known as vulnerability) can then be formulated as

$$P = \sum \beta_j P_j, \tag{2}$$

where P_j is the intensity of risk j, and β_j is the weight for risk source j.

Furthermore, D can be calculated as

$$D_i = (S_i/S)E_iF_i, \tag{3}$$

$$D = \sum (S_i/S)D_i = \sum (S_i/S)E_iF_i, \tag{4}$$

in which D_i is the Vulnerability Index of habitat i, E_i and F_i represent the Ecological Index and Fragility Index of habitat i, respectively; S_i is the area of habitat I, and S is the total area of a particular risk area (Xu et al., 2004, 2015; Wang and Zhang, 2007; Meng et al., 2015). This application has been widely recognized, and existing risk assessment models are only a special case of it (Power and McCarty, 2002; Fan et al., 2016; Balbi et al., 2016).

When conducting a regional ecological risk assessment, it is necessary to determine the integrated impact of multiple stressors on different ecosystems (Matthews et al., 2016; Liu et al., 2018a, 2018b), and it is particularly necessary to include an exposure-response analysis of the risk to different sub-regions (Zhu et al., 2018; Agathokleous et al., 2019). In this paper, we introduce an alternative ecological risk method based on a regional scale that emphasizes reducing linear impacts by

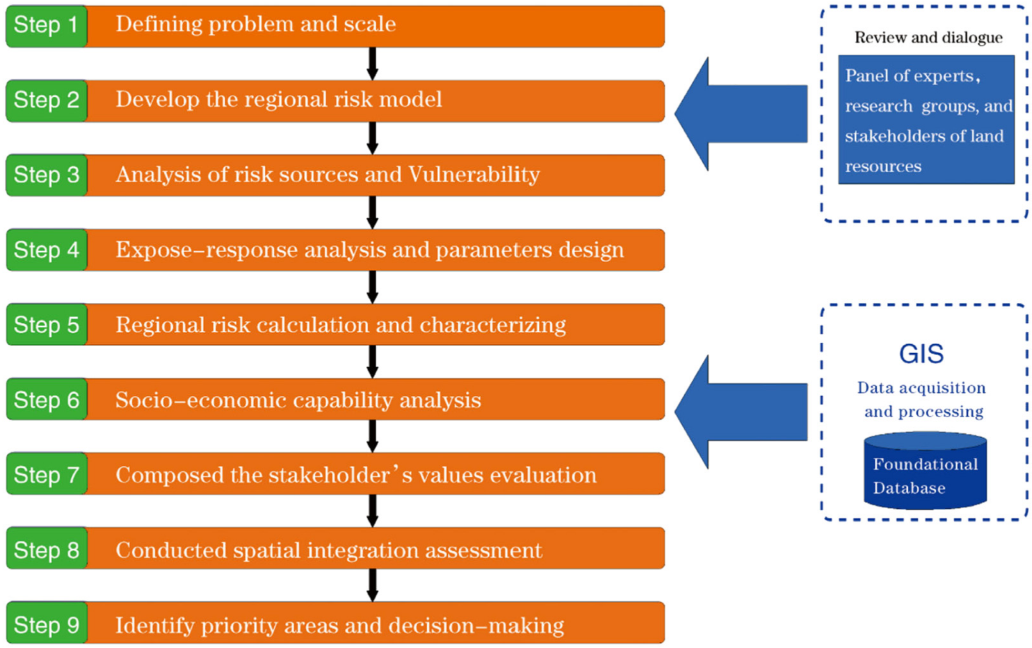

Fig. 3. Flow chart of regional ecological restoration of the Daye terrestrial ecosystem.

considering spatial heterogeneity and multiple stressors. The risk model is derived as follows:

1) In different sub-regions, the exposure to risk sources is varied to highlight spatial heterogeneity. For r regions, the exposure parameter of the risk source, j, is represented by C_{rj}.
2) Under different hazard levels, the response degree of the habitat is varied to highlight the nonlinearity of the effects. For example, in an ecosystem, there are class o habitats and n risk sources. For a risk source j, the risk intensity level is classified into m levels. When the risk source j occurs at maximum intensity, the potential loss of habitat i is D_i. When l level occurs, the loss is $\lambda_l D_i$, where λ_l is the ratio of the maximum level to the current level, and this reflects the specific loss degree. When the l^{th} level of the risk source j occurs, namely P_{jl}, the l^{th} level of the risk source j occurs in habitat i, and its habitat risk is calculated as $R = P_{jl}\lambda_l D_i$.

   Therefore,

$$R_{i,j,l} = \beta_j P_{jl} C_{rj} \lambda_l D_i, \quad (5)$$

where $R(i,j,l)$ is the risk value when the l^{th} level of the risk source j in the habitat i occurs; β_j is the weight of risk source j; P_{jl} is the intensity of the occurrence of the risk source j at the l level; C_{rj} is the exposure parameter of the risk source j in sub-region r; and $\lambda_l D_i$ is the vulnerability (or loss degree) of habitat i when the l level occurs.

2.3.2. Hazard analysis of risk sources

In addition to conducting field investigations, we undertook a literature review by searching and selecting related papers from the Web of Science (Xu et al., 2015; Pandey et al., 2016). Candidate risk sources of land degradation in Daye City were identified in Table 1 and under the following conditions: (i) we were familiar with the local economic development pattern, (ii) concerned about major pollutant-emitting enterprises, (iii) we conducted interviews with residents who had experienced past hazardous events, and (iv) we identified potential disturbances according to our knowledge (USEPA, 2000; Teng et al., 2014; Guo et al., 2017).

As some risk sources are more important than others, it is necessary to assign a weight to each risk source to enable an assessment of the intensity of compound actions (Table 1). Weights between risk sources can be calculated by comparing the relative importance between two factors at a time and then aggregating the results, as in the AHP method (Saaty, 1980; Souissi et al., 2019). The AHP is particularly applicable for use in evaluating problems in which qualitative factors dominate (Arabameri et al., 2019a, 2019b; Shariat et al., 2019). And we classified the source rank through adopting data segmentation function and the section assignment methods of ArcGIS software similar to most of the risk assessments (Table 2).

2.3.3. Vulnerability index analysis

Receptor vulnerability to risk sources can be identified as the sensitivity of a receptor to the degraded land, and it can be determined using the intrinsic characteristics of the receptors in the study area (Zabeo et al., 2011; Pizzol et al., 2011; Agostini et al., 2012).

2.3.4. Risk receptor

Receptors are seen as acceptors of risk actions in the risk assessment and can comprise sensitive biological species, population, habitats, and even the entire ecosystem (USEPA 2010; Stezar et al., 2013; Li et al., 2014; Cankaya et al., 2016). When conducting a regional risk assessment, habitat is defined as a group of ecological assets or entities at a regional scale (Landis and Wiegers, 2005; Li et al., 2010; Xu et al., 2015). In this study, habitats were classified according to the representative

Table 1
The weight design of risk sources in the Daye area.

Intensity of importance	Risk sources	Weights
1	Mining	0.123406
2	Urbanization	0.112187
3	Geological disasters	0.101988
4	Lake-area reclamation	0.092717
5	sewage emissions	0.084288
6	Storms and floods	0.076625
7	Solid waste pile	0.069659
8	Application of pesticides	0.063327
9	Aquaculture	0.057572
10	Acid rain	0.052336
11	Irrigation	0.047578
12	Agricultural intensification	0.043253
13	Application of fertilizers	0.039321
14	Biological resource consumption	0.035746

Table 2
Criteria for risk sources ranking and data processing in each sub-region.

Source	Description of risk hazards (Reference)	Data processing	Value range
Storms and floods	Destroys important habitats such as wetlands, arable land, forests, river banks and Changes the inherent depositional pattern (Reusch et al., 2005; Ayyub, 2014).	The frequency of occurrence of natural disasters (1950–2018). China Natural Disaster Dictionary (Hubei Volume).	1.06%
Geological disasters	Collapse, landslide, debris flow, ground collapse, goaf and ground cracking and so on that are important risk sources of land ecological degradation (Xu et al., 2012).	Area of geological hazard%: the proportion of area of geological hazard in sub-region.	0 0.001–0.003 0.003–0.016 0.016–0.034
Acid rain	Low-pH rainfall caused by industrial emissions and having negative impacts on soil quality (Larssen and Carmichael, 2000; Singh and Agrawal, 2008).	Frequency of acid rain. Published data of Daye city (2018).	51%
Urbanization	Extension of urban areas and urban area construction occupying land resources and removing habitats (Su et al., 2014; Weilenmann et al., 2017).	Urbanization intensity index.	0 0.087–0.096 0.097–0.178 0.179–0.286
Mining	Opening mines that reuslt in damage to earth surface, geodisasters and other environmental prolems. (Cao et al., 2016; Townsend et al., 2009; Zhuang et al., 2009).	Mining area%: the proportion of mining area in sub-regions.	0 0.001–0.004 0.004–0.028 0.029–0.053
Agricultural intensification	High-intensity and successive reclamation of land reducing soil fertility and productivity (Zhang et al., 2004).	Reclamation strength.	0 1.331–1.371 1.372–1.642 1.642–1.832
Lake-area reclamation	Change of lake areas into arableland reducing water habitats (Li and Zhang, 2015; Wang et al., 2008).	The intensity index of exploration for water area in sub-regions (km^2).	0 1.516–8.660 8.661–20.660 20.660–41.613
Aquaculture	Breeding fish and poultry in water areas that brings about eutrophication of water bodies. (Cao et al., 2007; Troell et al., 1999).	The proportion of aquaculture area in sub-regions.	0 0.006–0.043 0.044–0.139 0.120–0.676
Sewage emission	Emissions from factories polluting the surrounding air,water and soil. (Fang et al., 2013; Petersen et al., 2005; Xing et al., 2005).	Volume of wastewater emissions per year per km^2 in sub-region.	0 0.912–1.355 1.356–2.650 2.651–8.264
Solid-waste pile	Destroys the original landscape, exhausts land resources and deteriorates soil environment (Telles et al., 2007).	Volume of industrial solid waste discharge per year per km^2 in sub-region	0 0.001–0.002 0.003–0.014 0.015–0.029
Application of pesticides	Administration of pesticides that causes nutrient depletion and pollutes the food chain. (Fontcuberta et al., 2008; Ma et al., 2017).	Applied load of the crop area per km^2.	0 0.098–0.248 0.249–0.427 0.428–0.835
Application of fertilizers	Adminstration of fertilizers that brings about organic pollution (Carpenter et al., 1998; Hou et al., 2017).	Applied load of the crop area per km^2.	0 0.029–0.035 0.036–0.046 0.047–0.109
Irrigation	Irrational use of underground water that exhausts underground water and leads to soil salination. (Siebert et al., 2010; Yesilnacar and Yenigun, 2011).	Total consumption of agricultural water per year in sub-regions.	0 1–2,724,394 <6,626,258 <9,088,274
Biological resource consumption	Irrational felling of trees that leads to deforestation and soil erosion (Zipperer, 1993; Soane et al., 2012).	Total consumption per year per km^2 in sub-regions (including food consumption, lumbering, and grazing).	0 0.125–0.194 0.195–0.432 0.433–2.567

features of the land environment in the study area and by referring to typical terrestrial ecosystem classifications in China (Gao et al., 2013; Guo et al., 2017; Jin et al., 2019). Seven habitats were identified based on spatial remote sensing data as follows: (1) lakes, (2) rivers, (3) wetlands, (4) forests, (5) grasslands, (6) arable lands, and (7) urban and rural settlements. All seven of these habitat types were studied as risk receptors (Table 3).

2.3.5. Ecological Index of habitat

Different types of habitats have varying abilities to support biological diversity, protect living species, adjust to the climate, promote land productivity, and maintain the integrity of the associated ecological function, which can be represented by the Ecological Index (E_i) (Xie et al., 2013; Xu et al., 2015). In this research, to quantify the relative ecological function of the seven habitats in the terrestrial ecosystem within the study area, we assigned a value to every habitat, from 6 to 0, in descending order. Accordingly, the seven types of habitats were ranked for their ecological function as follows: lakes-7, rivers-6, wetlands-5, forests-4, grasslands-3, arable lands-2, and urban and rural settlements-1 (Table 3).

2.3.6. Fragility Index of habitat

Different habitats suffer differing amounts of damage under the same adverse impacts. The fragility index (F_i) denotes the extent to which a habitat is vulnerable, and a higher F_i indicates a higher potential ecological risk (Song et al., 2015; Fan et al., 2016; Zhang et al., 2018a, 2018b). Our research group selected relevant indicators to represent fragility based on the characteristics of habitat damage within the local traditional industrial and mining city. In this respect, eutrophication was representative of lake resources; the water quality (include the measurement of COD, ammonia nitrogen, and heavy metals) was representative of river pollution; the landscape fragmentation index was representative of the potential hazard to wetlands from the current spread of urbanization; the NPP index (Net Primary Productivity, NPP)

Table 3
Fragility index of habitat receptors and data processing in Daye area.

Habitats	Description of fragility index (Reference)	Data processing	Value range
Lakes	Eutrophication that deteriorates water quality and causes extinction of aquatic organisms (David et al., 2020; Liu et al., 2020a, 2020b).	The monitoring data of eutrophication in water bodies located in 37 sample monitoring points and for GIS spatial processing.	0 0.032–0.047 0.047–0.224 0.224–0.435
Rivers	The deterioration of water quality will threaten human health and affec agricultural production (Yao et al., 2015; Meng et al., 2019).	Determined the level of water quality degradation (i.e., heavy pollution, moderate pollution, and light pollution), and performed GIS spatial processing.	0 0.001–0.002 0.00–0.006 0.007–0.010
Wetlands	Landscape fragmentation will bring disfunction of the wetlands ecosystem and biodiversity decreased (Zheng et al., 2017; Lam et al., 2018).	The fragmentation indicator was calculated using a spatial distribution map of patch density.	0 0.003–0.005 0.005–0.007 0.008–0.011
Forests	Decline in Net Primary Productivity (NPP) will spoil food safety for humans and other creatures (He et al., 2017; Pellegrini et al., 2018; Turner et al., 2018).	In ArcGIS 10.2, NPP data are graded and assigned according to the standardized grading method to form the situation of primary productivity of forester ecosystem in Daye city.	0 0.078–0.139 0.140–0.376 0.377–0.537
Grasslands	Soil erosion that exhausts land resources and deteriorates soil environment (Li et al., 2018; Liu et al., 2020a, 2020b).	According to the national industry standard sl190–96 soil erosion classification to divided into four grades: slight, mild, moderate and severe.	0 0.001–0.012 0.012–0.029 0.029–0.0460
Arable lands	Organic matter runoff that leads to soil nutrient depletion and even threaten agriculture security (Cowie et al., 2018; Morales and Zuleta, 2019).	The content of soil organic matter was investigated for presenting the degradation in arable lands.	0 0.001–0.305 0.306–0.342 0.343–0.511
Urban and rural settlements	Population aggregation will pose higher land consumption and make development unsustainable (Xu et al., 2011; Zhao et al., 2013; Huang et al., 2016).	Population aggregation as an important indicator was used to represent the ecological process of the urban and rural settlements.	0 0.066–0.069 0.069–0.121 0.122–0.223

was representative of the production of the forests habitat; soil erosion (minute, slight, average, and severe) was representative of the loss of water and soil within a grassland habitat; the soil organic matter contents were representative of the infertility of arable land; the population aggregation was used to measure the bearing capability of regional urban and rural settlements (Table 3).

2.3.7. Expose-response analysis

Expose-response analysis is used to identify relationships among risk components and calculate them accurately (USEPA, 2011; Kanwar et al., 2015; Sperotto et al., 2016). An expose-response analysis was thus conducted with respect to the main hazard sources and release mechanisms, and the key exposure-response pathways and the vulnerability of the receptors were analyzed and discussed. Two analysis (parameter) layers were designed to enable the assessment to be conducted and characterize the interactions between risk sources and habitats.

The exposure analysis determined whether or not the source was likely to cause habitat damage (Yao et al., 2015; Yang et al., 2018). In different sub-regions, the exposure of risk sources varied with respect to the spatial heterogeneity. For r regions, the exposure parameter of the risk source j was considered to be C_{rj}. In our study, the degree of exposure that the risk source had on the habitat was represented using 3, 2, 1, and 0, which indicated “strong,” “medium,” “weak,” and “no effect,” respectively (Appendix 1). The effects of the risk source on the habitat varied with respect to the different exposure pathways in the different sub-regions, which also illustrates the effect of spatial heterogeneity (Xu et al., 2004; Perez-Minana, 2016; Cao et al., 2019). For details, see the model derivation description.

The response analysis focuses on the degree of habitat response, which differs under different damage intensities and thus shows a nonlinear effect. The relationships between hazard states and habitat vulnerability were quantified within the parameters of the ratio (for details, see the description of the model derivation). In addition, to ensure that the states of the hazard and habitat vulnerability interacted logically (and to avoid bias), empirical data, laboratory data, past experience, expert opinions, and results of the literature review were used to estimate the conditional parameters (Li et al., 2018; Guo et al., 2017, 2020). For hazards occurring at one of four levels (high, medium, low, and none), the parameter λ_l was assigned as 1, 2/3, 1/3, and 0, respectively, to characterize the ratio of the maximum level to the current level (Appendix 2).

2.4. Socio-economic capability analysis

A socio-economic analysis can determine the advantages of restoring the ecology at a regional level. We selected five indicators for use in the socio-economic analysis, which assesses the capabilities of the different sub-regions to ecologically restore degraded land, and these are as follows: the land improvement intensity reflects the annual reclamation efforts made by the government; GDP reflects the strength of the regions' finances; road density reflects the volume of traffic; the quantity of soil reserves used for filling reflects advantages when conducting land reclamation projects; the labor force reflects the available labor. As this is a traditional industrial and mining city with exhausted resources, it has a significant outflow of young labor.

2.5. Stakeholder assessment

In our study, it was necessary to identify the land degradation characteristics within the traditional industrial and mining city to enable appropriate ecological restoration to be planned (Hou et al., 2014; Dick et al., 2018). Our study team cooperated with the Daye Land Resources Bureau, the Environmental Protection Agency, Wuhan University, and Hubei Normal University to investigate the amount of environmental damage in degraded areas that had experienced ecological destruction from mining over a prolonged period. To reflect practical difficulties in restoring the ecological environment with respect to the land resources, four indicators were selected and included in the stakeholder assessment: the type of damage, the degree of damage, the amount of land available, and the size of the area.

The GIS-MCDA approach is quite effective for use in structuring problems, dealing with various components, processing multi-type data, and integrating expert judgments to determine the most appropriate suggestions and requirements (Luyet et al., 2012; Malczewski and Rinner, 2015; Thokala and Madhavan, 2018). We thus applied this approach to our stakeholder assessment, and it assisted in highlighting the advantages of using spatial data when conducting ecological restoration during the transition period of a resource-exhausted city (as described in the previous data source).

The assessment of different stakeholders was conducted to determine the restoration constraints from industrial sites and mines with respect to damaged land. First, using the MCDA method, the limit levels of restoration were determined and divided into four levels: extremely high, high, medium, and low. The four above-mentioned indicators (the type of damage, degree of damage, amount of land available, and the size of the area) considered in the stakeholder evaluation were used to determine restrictions to ecological restoration (Table 4). In addition, the AHP method was applied to determine the weight of indicators included in the evaluation. Secondly, the AHP was also used to determine the evaluation weight when identifying the type of damage occurring on reclaimed land (such as occupation, excavation, goaf, collapse, excessive penetration, water and soil loss, and heavy metal pollution, etc.). The degree of damage of reclaimed land was represented by scores of "relatively severe, medium, and slight" and these were assigned values of 4, 3, 2, and 1, respectively. Third, by referring to the Urban Development Guidelines 2025, the original land-use type, the damage condition, and public opinion, the experts outlined the aims of recovering the damaged land by creating cultivated land, forest, or construction land. Moreover, the different social, ecological, and economic benefits of the different land types were considered. For example, restoring and utilizing construction land provides great economic benefits. The social, ecological, and economic benefits were given a weight, and land availability was then evaluated. In addition, damaged areas were graded by natural breaks in GIS operation (Table 4). Finally, the constraint levels of ecological restoration were further evaluated using "extremely high, high, medium, and low", and the statistical information obtained was spatialized.

2.6. Integrated assessment

The aim of conducting an integrated assessment is to identify priority areas for recovery. We evaluated the viability of conducting ecological restoration on a regional scale by considering regional ecological risks, the feasibility associated with social-economic conditions, and the values of stakeholders (Huang et al., 2011; Li et al., 2014; Khosravi et al., 2019).

The TOPSIS technique is commonly used when conducting a multi-objective decision analysis of limited programs and is also widely applied in many fields such as benefit evaluation, health decision-making, resource management, and nature hazard analysis (Nyimbili et al., 2018; Arabameri et al., 2019a, 2019b). The basic concept of TOPSIS is that it uses the cosine method and the normalized initial data matrix to find the best and worst solutions out of a limited number, and these are represented by the best vector and the worst vector, respectively (Kumar et al., 2017; Peng and Selvachandran, 2019). The distance between each alternative and the best and the worst solution is then calculated to obtain the relative closeness of each alternative scheme to the optimal solution, and the result is used to determine whether the evaluation is good (Sun et al., 2017; Meshram et al., 2020).

Based on the TOPSIS approach, we conducted a spatial integration assessment to determine appropriate ecological restoration intervals for the terrestrial ecosystem. The process used was as follows: first, three elements (regional ecological risk, social-economic status, and the evaluation of different stakeholders) were treated using attribute assimilation and the data were normalized. Second, the positive ideal (best) and negative ideal (worst) solutions were determined. The distances between each alternative and the best and worst solutions were then calculated, and the proximity between each of the alternatives and the optimal solution was also calculated. Finally, the alternatives were ranked in order of preference from the most preferred to the least preferred feasible solution. The ecological restoration ranges of the terrestrial ecosystem were then obtained, such as the "top priority rectification area," "high priority rectification area," "medium priority rectification," and "low priority rectification area". In addition, decision-makers can see a spatial visualization of the results to make appropriate decisions about regional ecological restoration and enable precise management.

3. Results

3.1. Spatial distribution and characteristics of eco-risk

The risk levels were calculated using a risk model and then represented on a grid using 1 × 1 km grid cells (Fig. 4). Results showed that the extremely high-risk areas were found in 4.75% of the grid cells in the eastern region (spanning 73.86 km^2), 10.36% of grid cells in the central region (161.1 km^2), and 6.62% of cells in the western region (102.94 km^2). These were distributed over an ore belt and they highlight the serious deterioration of terrestrial ecosystems in the Daye area. High risk areas occurred in 5.15% of all grids in the eastern industrial zone (80.05 km^2) and 23.37% of all grids in the southern forest area (363.40 km^2). Areas of moderate risk were found in 43.53% of all grids within the eastern and central regions (676.89 km^2). Areas of low risk were found in most of the northwestern great natural wetlands (16.25% of all grids spanning 252.68 km^2), and the northeastern region (17.31% of all grids spanning 268.20 km^2), which is predominantly water area.

3.2. Socio-economic conditions and stakeholders assessment

Sub-region 2 has the strongest socioeconomic potential to carry out the restoration programs of terrestrial ecosystems. It is a traditional iron

Table 4
Operational procedures and data processing in Stakeholder assessment.

Plot numbers	Type of damage (importance)	Degree of damage (values)	Amount of land available (weights)				Size of the area	
			Land types were considered	Social benefits (0.3655)	Ecological benefits (0.3323)	Economic benefits (0.3021)	Value range and assignment	Area and rank
FK001	Goaf (1)	Severe (4)	Construction land	2	1	3	0.003695–2.598581 (1)	0.57 (1)
FK002	Landslide (6)	Medium (3)	Cultivated land	3	2	1	2.598582–7.679969 (2)	0.66 (1)
FK003	Debris flow (7)	Medium (3)	Forest	2	3	1	7.679970–19.874291 (3)	5.26 (2)
FK004	Exhaustion of water source (9)	Low (2)					19.874292–43.710134 (4)	12.2 (3)
FK005	Collapse (2)	Slight (1)						28.6 (4)
FK006	Heavy metal pollution (3)	Slight (1)						35.8 (4)
…	Excavation (4)	Severe (4)						…
	Water and soil loss (10)							
	Occupation (11)							

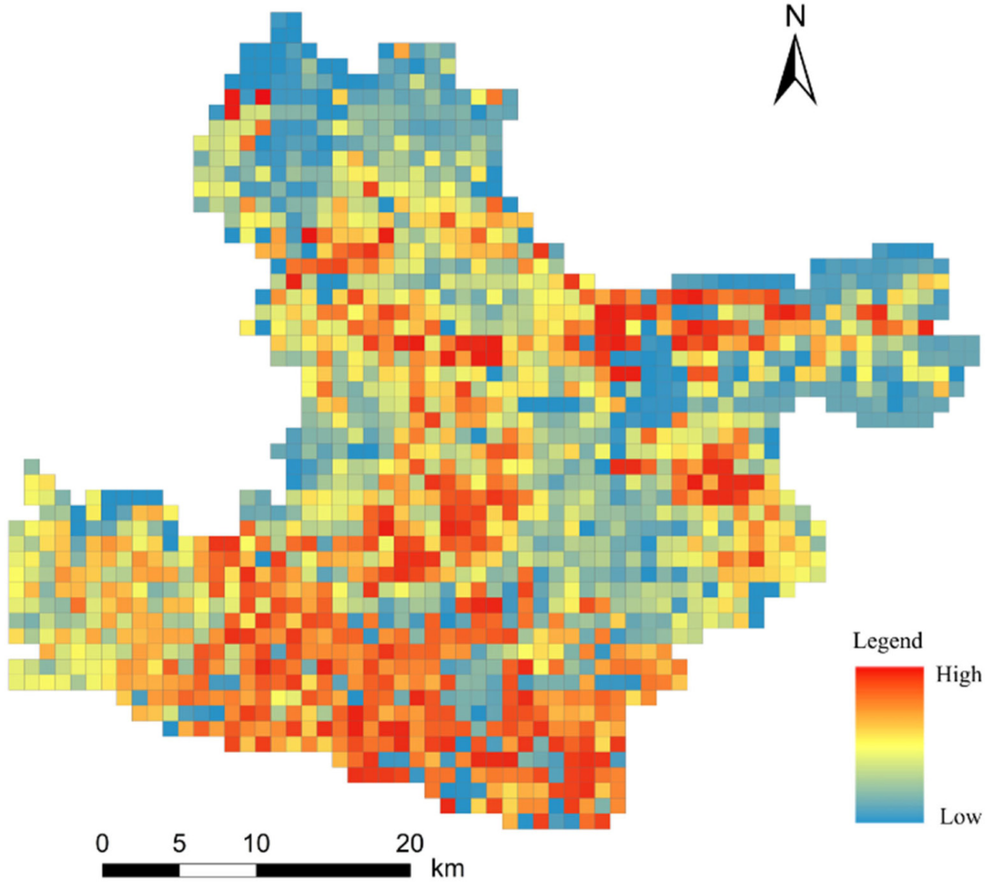

Fig. 4. Graph showing risk grades when conducting a regional risk assessment of the terrestrial ecosystem in the Daye area.

ore mining area with the highest local fiscal revenue (Fig. 5). Sub-region 5 ranked second; although this region is located in the south and is an agricultural and forestry area, it has adequate soil-filling reserves. Sub-regions 6 and 4 are traditional copper mining and smelting processing zones located in the middle of the area, and they have lower socio-economic suitability. Land remediation in these areas has been stagnant because of long-term environmental degradation and land disputes between the government, mining companies, landowners, and local residents. In addition, most of the industrial and mining enterprise employees are foreigners and there a young, local, labor force is lacking.

The stakeholder assessment generally reflected the characteristics of industrial and mining cities that have undergone ecological degradation (Fig. 6). Fig. 6 shows that 17.85% of the regions that have a very low willingness to be restored are distributed in the iron ore region in the northwest, and 23.30% are located in the central mining processing industry belt. This distribution relates to large-scale mining, collapse, excavation, and other geological disasters caused by long-term mining, which result in huge restoration costs. In addition, the metallurgical processing belts experienced serious environmental deterioration and the land was subjected to ore washing, beneficiation, smelting, processing, and transportation. The surrounding habitats were thus exposed to the threat of heavy metal pollution for a long time, and the land has high concentrations of Cu, Pb, Cd, Hg, and As, which poses a high risk to human health. Therefore, the current land restoration potential is very low.

3.3. Setting priority options

Based on the TOPSIS method, priority levels for ecological restoration were divided into: top priority rectification areas, high priority rectification areas, medium priority rectification areas, and low priority rectification area (Fig. 7). In the figure, the areas close to the color green are the restoration areas of high priority, while those close to red are restoration areas of low priority. Of these, the top priority rectification areas are mainly distributed in northeast and northwest regions in an area spanning 358 km^2. In addition, 182 km^2 of farmland can be re-cultivated after improvement. The high priority rectification areas are obviously concentrated in the central traditional mining areas, which is an area spanning 226km^2. The medium priority rectification area is mainly distributed in the central and eastern areas, which are large areas of arable land, and large areas of forest land in the southern regions covering 243 km^2 and 362 km^2, respectively. Furthermore, 195 km^2 of the low priority rectification area is land that experiences geological hazards and heavy pollution and it is difficult to make associated restoration plans at present.

4. Discussion

The RRA methodology developed in this study is an explanatory tool that identifies priority areas with respect to ecological restoration of the terrestrial ecosystem, and it can be used to make decisions and be employed in land-resource management and research.

Use of the RRA approach and GIS methods that we developed for use as decision-making tools to determine the priorities and feasibilities of restoring the ecology to the terrestrial ecosystem on a regional scale can be considered a new approach for use in land-resource management research. Eco-risk research reveals the land degradation process on a regional level, and is thus useful for identifying ecological recovery mechanism (Agostini et al., 2012; He et al., 2020). The multi-factor investigation employed in

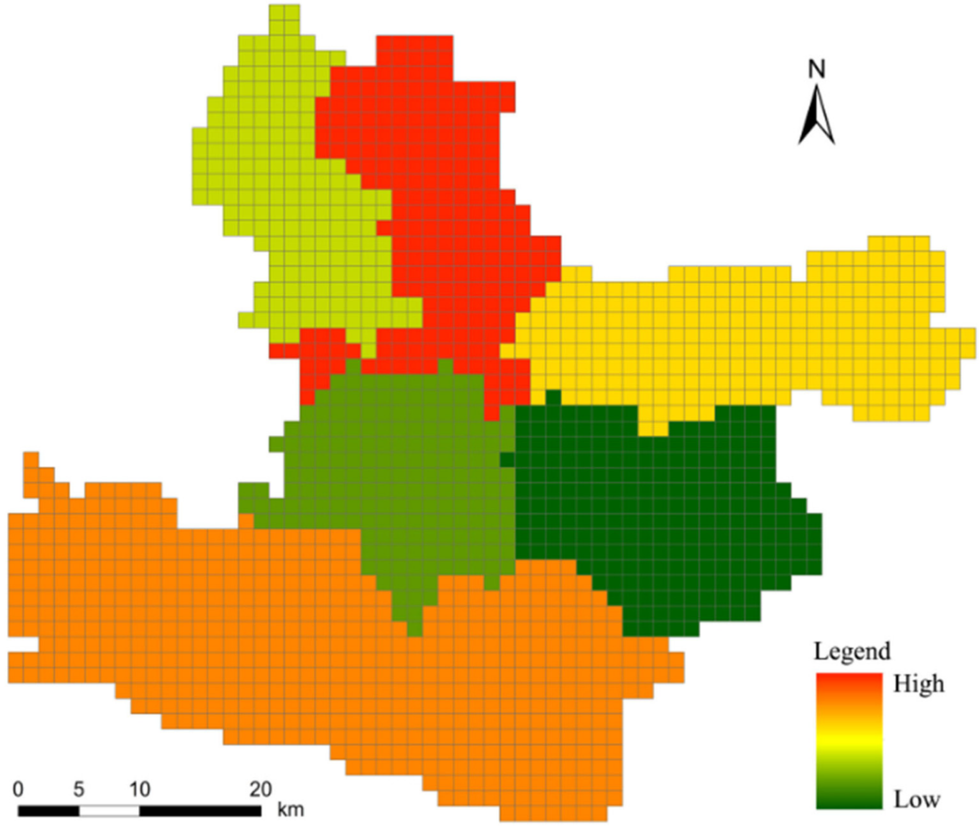

Fig. 5. Ecological restoration capabilities of different sub-regions in the Daye area.

the present research can be used to comprehensively restore an entire terrestrial ecosystem. The importance of decision-making is dependent on conducting an entire analysis of the degraded land on a regional scale. In addition, the nonlinear model reduces the uncertainty involved in risk calculation caused by habitat diversity and spatial heterogeneity in terrestrial ecosystems.

The participation of different stakeholders from a diverse range of backgrounds (assessors, experts, officials, entrepreneurs, and farmers) facilitates communication and can mean that suggested plans are more likely to be publicly acceptable. With the advantages of using the MCDA method for processing and transforming different spatial data when conducting quantitative or semi-quantitative research, multiple opinions are integrated and evaluation criteria can be weighed according to their importance (Huang et al., 2011; Nie et al., 2018). In addition, the TOPSIS technique provides greater flexibility for dividing ecological restoration intervals on a regional scale (Nyimbili et al., 2018; Wang et al., 2020).

It is useful to understand the socio-economic conditions to adjust the measures required to local conditions and enable the ecological restoration of the terrestrial ecosystem over a larger area. Recovery planning should be implemented using appropriate management measures according to current conditions. In this study, priority areas for ecological restoration were identified within different regions and appropriate strategies suggested according to the various stages. It is significant to support decision-makers in avoiding extensive investigations and incurring unnecessary costs. In addition, identifying such areas is conducive to formulating long-term sustainable restoration plans for the whole terrestrial ecosystem.

Motivations varied by environmental degradation patterns, stakeholder types, and transformation of urban development for eco-restoration terrestrial ecosystem in these industrial and mining cities. Most approaches were aimed at seeking the decision tools for large-scale ecological restoration to obtain the environmentally safe, localization, and economic profitable strategies. The research was faced with the following difficulties. The first-line environmental investigation of land ecology takes a long time (Guo et al., 2020; Tian et al., 2020). Different types of data come from experts with different backgrounds, which is difficult to be quantified and spatialized later. Large-scale recovery was limited by the social-economic conditions of the local government. As for the optimum of environmental benefit and cost benefit was still difficult to measure. At the same time, we found that research has paid less attention to the maintenance of human health. In other words, what is important and reflect what people care about in their own homes. Therefore, future research should promote the human welfare in terrestrial restoration. Finally, the recovery of the whole terrestrial ecosystem remains to be verified, for example, to ensure the accuracy of the restoration of system service functions.

Large-scale ecological restoration of a terrestrial ecosystem requires ecological modeling to identify problems and impact factors and to perform hazard analysis. This is conducive to the decision making for functional recovery of the whole system. Regional ecological restoration should be based on locational conditions, and the recovery planning should be categorized according to the different characteristics of the environment. That is why our study area has been divided into six sub-regions based on their respective economic, ecological, and geographical features. Due to the complexity and long-term nature of terrestrial restoration, earlier socio-economic assessment is necessary, including capital, human resources and transportation, etc. We know that the issue of land resources involves numerous conflicts and concerns different interest groups. Therefore, encouragement of participation by

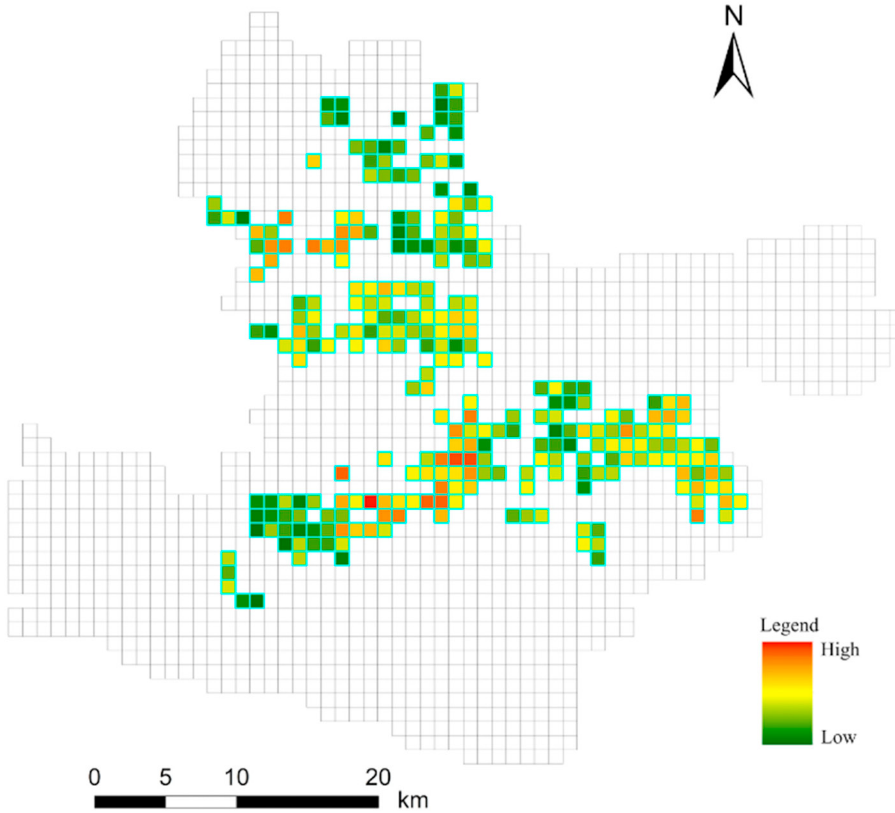

Fig. 6. Levels of constraint relating to the ecological restoration potential of degraded land in the Daye area.

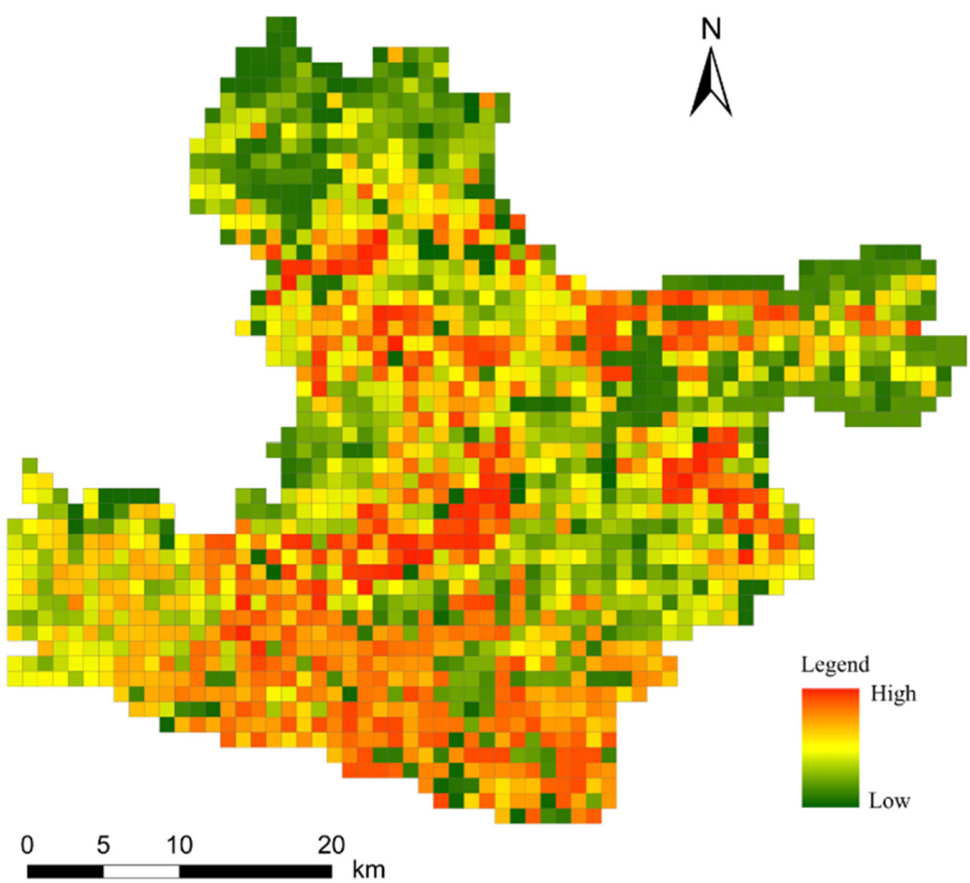

Fig. 7. Priority ecological terrestrial ecosystem restoration grades in the Daye area.

different stakeholders is proposed so that decision-making will be widely accepted. However, the policy-makers' strategies derived from our approach are still subject to test and confirmation in practice of terrestrial management. In particular, we should focus our attention on the investigation of first-line resources and the environment in resource-exhausted cities according to their respective specific situations in order to implement timely measures, and we must not be confined to experimental simulations.

5. Conclusions

In this study, a spatial regional risk assessment methodology was established as a decision-making tool for use in prioritization of the ecological restoration of a terrestrial ecosystem on a regional scale. To assist policymakers in their work, priority areas were identified and appropriate land rehabilitation methods were suggested. These methods were to reduce regional ecological risks, and to propose the feasibility of implementing rehabilitation with respect to socio-economic conditions and the orientation of different stakeholders concerning the issue of the land resources. We believe that the methods presented here are of practical significance for planning the ecological restoration of terrestrial ecosystems and ensuring the sustainable use of resources when transforming urban functions. Future work should to flexible application in spatial visualization, combined with other algorithms to improve their capabilities, and fully exploited the potential of RRA methodology to modeling multiples factors on a larger scale. In particular, it is necessary to identify better quantitative methods for use in conducting an exposure-responses analysis with optimized parameters and making risk calculations. It is also necessary to focus on different types of stakeholder modeling to determine participation in environmental projects on a regional scale. Such as through evolutionary algorithm embed for promoting high predictive accuracy for maximize the benefit of stakeholder assessment. In addition, remote sensing technology should be used to assist in identifying priority areas for large-scale ecological restoration of terrestrial ecosystems. Furthermore, the validity of the model and method employed here also need to be further tested using other terrestrial ecosystems to determine their wider applicability.

CRediT authorship contribution statement

Kai Guo: Conceptualization, Methodology, Resources, Writing - original draft. **Xinchang Zhang:** Software, Funding acquisition, Project administration. **Jiamin Liu:** Investigation, Formal analysis, Data curation. **Zhifeng Wu:** Validation, Supervision, Project administration. **Yiyun Chen:** Investigation, Resources, Writing - review & editing, Supervision. **Min Chen:** Investigation, Software, Data curation. **Kexin Zhang:** Formal analysis, Visualization, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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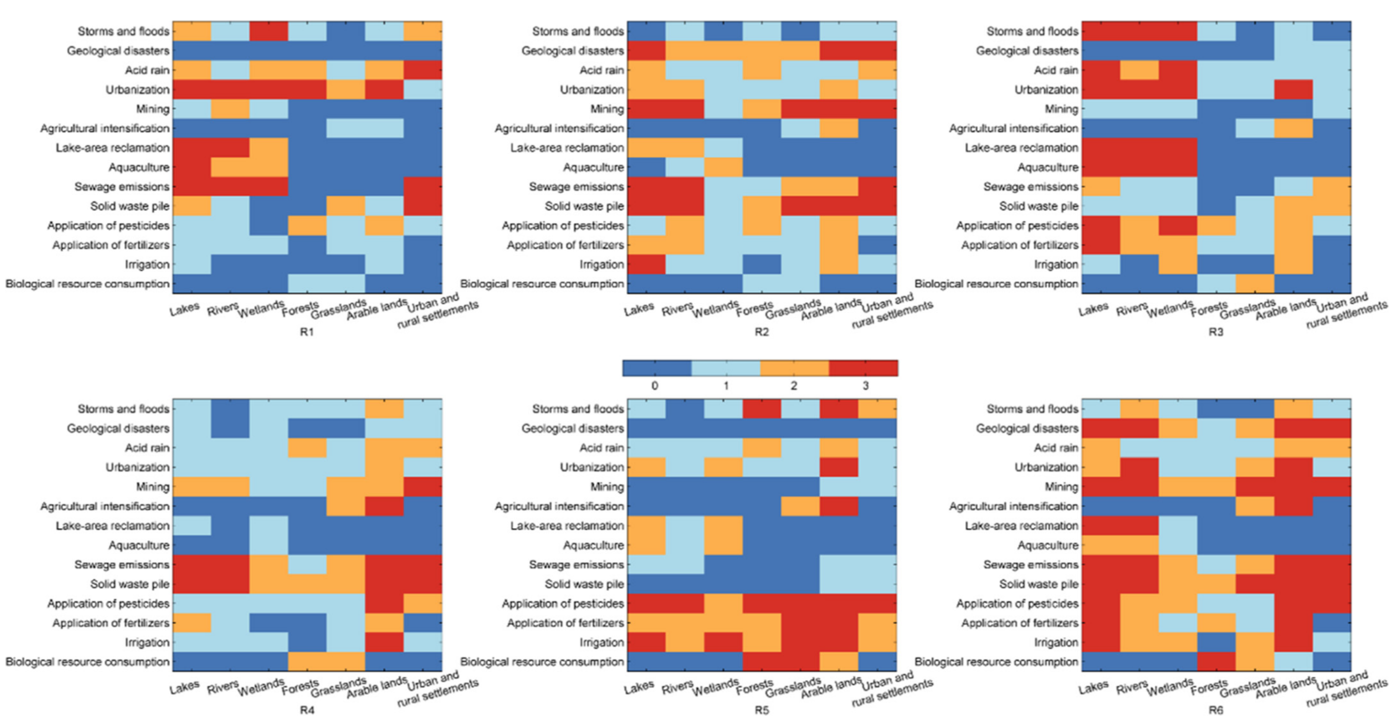
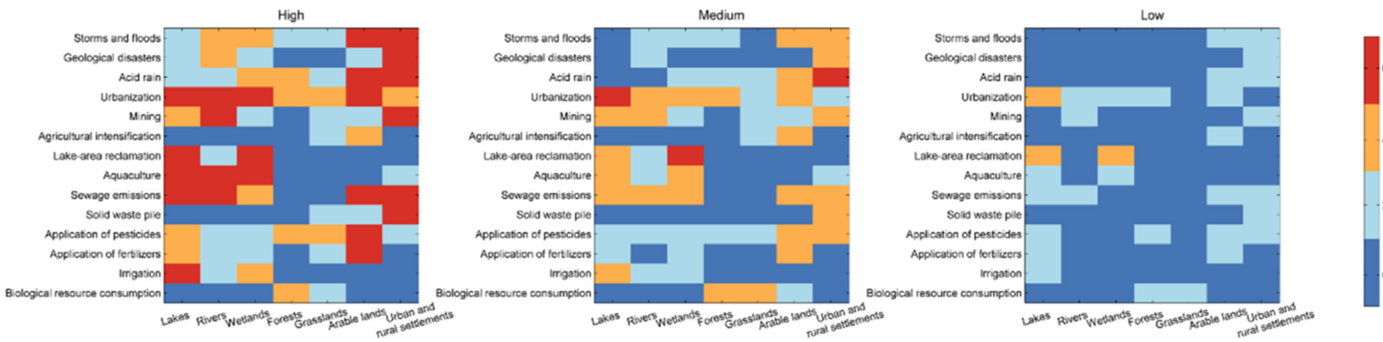
Appendix A. Two parameter layers were designed to expose-response analysis



Appendix 1. Exposure parameter designed for different sub-regions in the Daye area.



Appendix 2. Response parameter designed in the Daye case study.

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