# Regional Land Eco-Security Evaluation for the Mining City of Daye in China Using the GIS-Based Grey TOPSIS Method

**Xinchang Zhang [1], Min Chen [2], Kai Guo [1,*], Yang Liu [2], Yi Liu [3], Weinan Cai [1], Hua Wu [1], Zeyi Chen [4], Yiyun Chen [4] and Jianguo Zhang [5]**

[1] School of Geography and Remote Sensing, Guangzhou University, Guangzhou 510006, China; zhangxc@gzhu.edu.cn (X.Z.); caiwn@e.gzhu.edu.cn (W.C.); 2111801054@e.gzhu.edu.cn (H.W.)

[2] Guangzhou Urban Planning & Design Survey Research Institute, Guangzhou 510060, China; 2018282050161@whu.edu.cn (M.C.); liuyang@gzpi.com.cn (Y.L.)

[3] School of Public Administration, Guangdong University of Finance & Economics, Guangzhou 510320, China; liuyi@gdufe.edu.cn

[4] School of Resource and Environmental Sciences, Wuhan University, Wuhan 430079, China; chen_zy@whu.edu.cn (Z.C.); chenyy@whu.edu.cn (Y.C.)

[5] Hunan Botong Information Co., Ltd, Changsha 410021, China; zhjg0731@163.com

* Correspondence: guokai@gzhu.edu.cn; Tel.: +86‑135‑0719‑2439

**Abstract:** Regional ecological security assessment is a significant methodology for environmental protection, land utilisation, and human development. This study aims to reveal the regional constraints of ecological resources to overcome the difficulties and complexities in quantification of current models used in land ecosystems. For this purpose, the technique for order preference by similarity to an ideal solution (TOPSIS) was linked to a grey relational analysis and integrated with a geographic information system. The obtained method was used to construct a land eco-security evaluation on a regional scale for application in a traditional mining city, Daye, in central China. Parameter analysis was introduced to the method to produce a more realistic spatial distribution of eco-security. Subsequently, based on the pressure–state–response framework, the eco-security index was calculated, and the carrying capacity of land resources and population for each sub-region were analysed. The results showed that: (i) very insecure and insecure classes comprised 5.65% and 18.2% of the total area, respectively, highlighting the vulnerable eco-environmental situation; (ii) moderate secure classes areas comprised a large amount of arable land, spanning an area of 494.5 km2; (iii) secure areas were distributed in the northwest, containing mostly water and wetland areas and accounting for 426.3 km2; and (iv) very secure areas were located on the southeastern region, involving traditional woodland with a better vegetation cover and an overall higher eco-environmental quality. In addition, for each sub-region, the extremely low and low ecological security areas were mainly arable and urban lands, which amounted to 305 and 190 km2, respectively. Under the current ecological constraints, sub-region 1 cannot continue supporting the population size in Daye City. The present results demonstrate the accuracy of our methodology, and our method may be used by local managers to make effective decisions for regional environment protection and sustainable use of land resources.

**Keywords:** regional land eco-security; TOPSIS; grey relational analysis; land ecosystem

## 1. Introduction

Regional land ecosystems are important life-support systems in the world, and they are essential for ecological performance and social and economic development [1–3]. However, with the rapid development of urbanisation and industrialisation and the changes in human lifestyle, ecosystems have significantly degraded. In this context, land deterioration on the regional scale is detrimental to humans and the environment. The

damages are loss of important habitats leading to biodiversity decrease and species extinction [4,5]; serious human health threats resulting from soil and water contamination with heavy metal, organic matter, and pathogens [6,7]; lower supply of essential goods due to the reduction in land productivity caused by soil depletion, soil acidification, and soil erosion [8–10]; and large-scale ecological refugee migrations caused by geological disasters, earth's surface destruction, and spread of desertification under climate change [11]. These impacts have produced significantly negative effects on the sustainable development of regional economies and human beings, and have stimulated potential political and social conflicts.

Therefore, in the face of the increasingly global land degradation, there is an urgent need for restoration planning and guided urban programs and land development, for which regional land ecological security assessment should be considered [12–14]. In recent years, various methods and technologies have been utilised together to evaluate and predict land eco-security. For example, the monitoring of ecological degradation and early warning [10,15], identification of driving forces of eco-security patterns [16], research on the issues of survival of human beings and sustainable development of urban areas [1,17], environmental impact assessment for target development plans [18], promotion of biodiversity conservation [19,20], identification of the carrying capacity of land resources [21,22], design of regional economic plans [23], and various eco-security index systems suggested for background database management [23,24]. The final goal is to facilitate the service functions of land ecosystems and to ensure sustainable development of the economy and society.

These previous models and tools have some disadvantages when applied to research on regional land ecosystems. Firstly, they tend to focus on mono-factor studies, which cannot reflect the whole state of ecosystem degradation and may not be able to provide motivation for stakeholders to adopt measures for comprehensive protection of the regional ecosystem. Secondly, the procedure of protection lacks the capability of larger-scale analysis, especially in administrative areas, which require tens to hundreds of factors for the assessment of regional eco-security status. The complexity of land problems on a large scale involves such factors as environment, resources, social–economic field, and government policies, etc. These determine the evaluation of regional land eco-security to be a mufti-criteria decision-making problem. Thirdly, they are not able to process or transform different spatial data, such as quantitative, semi-quantitative, or qualitative data. Fourthly, problems resulting from ecological degradation closely concern regional economic development, and evaluation tools in this field have to fit in with frequently updated ecological resource datasets. Finally, the assessment of regional eco-security still needs advanced software and operational platform support. TOPSIS) is a discrete mufti-criteria decision analysis method that encompasses a set of techniques to support decision-making processes [25,26]. Thus, we investigated TOPSIS combined with the grey relational analysis (GRA).

In performing a multi-objective decision analysis of limited programs, the TOPSIS technique is often used, and the technique is extensively applied in such fields as benefit evaluation, health decision-making, resource management, and natural hazard analysis [27–29]. In TOPSIS, the cosine method and normalized initial data matrix are used to identify the best and worst choices from a limited number of solutions, which are represented, respectively, by the best and worst vectors [30,31]. Then, calculation of the distance between each alternative and the best and the worst solutions is performed in order to identify the relative closeness of each alternative scheme to the optimal solution, which is used to determine the adequacy of the evaluation [32,33]. In recent years, to effectively solve multi-criteria decision analysis problems from different angles, there has been an increasing number of studies concerning the modified TOPSIS method.

The method of Grey–TOPSIS (grey correlation analysis, GRA) measures the correlation among factors based on the similarity or difference in the development trend among them [34,35]. It is commonly constructed according to the spatial distance variables ex-

tracted from remote sensing imagery and geographic information system (GIS) data [36,37]. This method is able to process multi-type data in input–output and still works when the data-collection environment is not sufficiently ideal. This facilitates many applications in large-scale complex ecological ecosystems, for which data information is relatively scarce [38,39]. For massive calculations, it can be easily combined with other algorithms to provide a globally optimal solution [31,40]. This is also conducive to the construction of a large-scale resource decision system to serve government departments. In particular, the grey correlation analysis can be used to compare the advantages and disadvantages of the same grade. However, information regarding the utilisation of the integrated approach for combining the TOPSIS with GRA method in the study of regional land eco security is limited.

This present research was to develop a methodology for land eco-security evaluation and mapping by means of GIS modelling, integrated with GRA and TOPSIS, and the methodology was performed in Daye, a previously mining city in China. The carrying capacity of the land resources and population for each sub-region was identified, and a sustainable urban planning scheme was proposed. The results would be useful to support decision makers in identifying warning areas with land deterioration and managing regional eco-security.

## 2. Materials and Methods

### 2.1. Description of the Study Area

Daye City is located in the southeast of Hubei Province in Central China (114° 31–115° 20 E, 29° 40–30° 15 N) near the Yangtze River (Figure 1). This area is rich in mineral deposits which have given rise to well-developed mining and metallurgy industries. The ecosystem in the area includes lakes, rivers, forests, mines, arable lands, gardens, and urban and rural residential areas. The present study here covers an area of 1566.3 km². The city, located in the 'metallurgy corridor' of Hubei Province, is rich in mineral deposits with well-developed mining and metallurgy industries. According to the County Basic Competitiveness Top 100 Counties (small and medium-sized cities in China), Daye has devolved in terms of comprehensive strength in the last few years. The industrialisation has increased significantly in the area where the ecosystem has suffered, with soil contamination, water pollution, and loss of arable land, which have led to dysfunctional ecosystem services. To ensure that accurate decisions are made for the ecological protection of the regional ecosystem while incorporating an eco-security perspective, this study performed a regional eco-security assessment.

### 2.2. Framework of the Regional Land Eco-Security Assessment

As of 2020, China started its "14th five-year plan" period [41,42]. Daye is a traditional mining industrial city, which is also confronted with the dual-challenges of economic transition and territorial space planning [43–45]. In this study, firstly, we considered the characteristics of regional land degradation to suggest an indicator system for the land eco-security assessment and then used the pressure–state–response (PSR) approach. Secondly, the analytical hierarchy process (AHP) was used to assign the weights of each evaluation element. Thirdly, the Grey–TOPSIS method was modified by introducing parameter analysis, and it was then applied to ArcGIS 10.2. The land eco-security index was calculated and classified into different levels by spatial mapping on a regional scale. Fourthly, the carrying capacity analysis of land resources and population for each sub-region were designed under the eco-security constraint. Finally, priority countermeasures were suggested for different eco-security areas on a regional scale. The procedures used in our approach are presented in Figure 2.
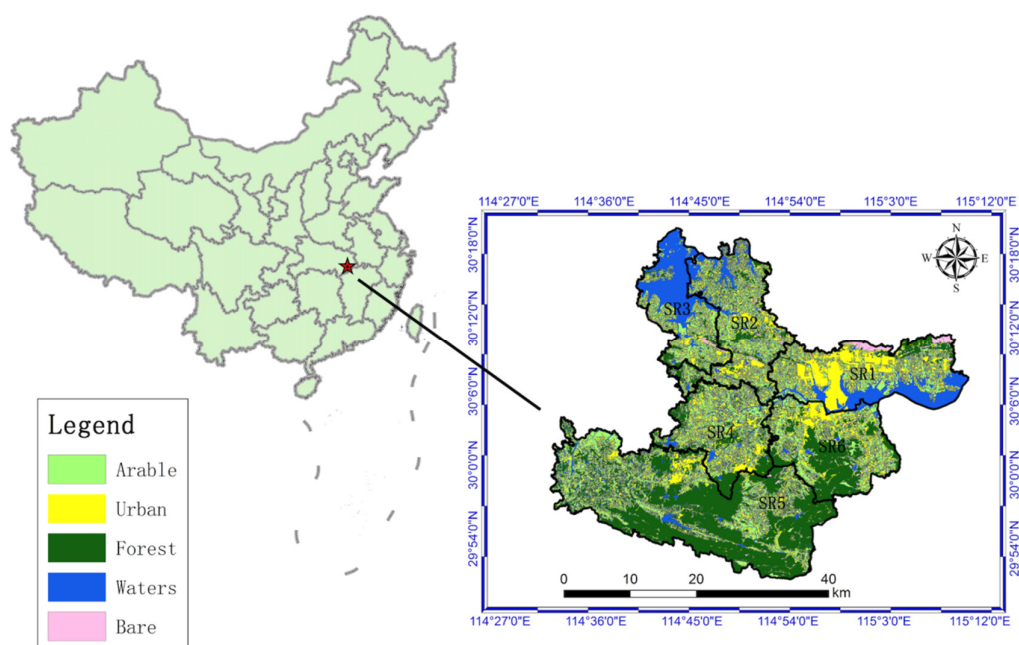
**Figure 1.** Land use map of Daye City and its sub-regions.
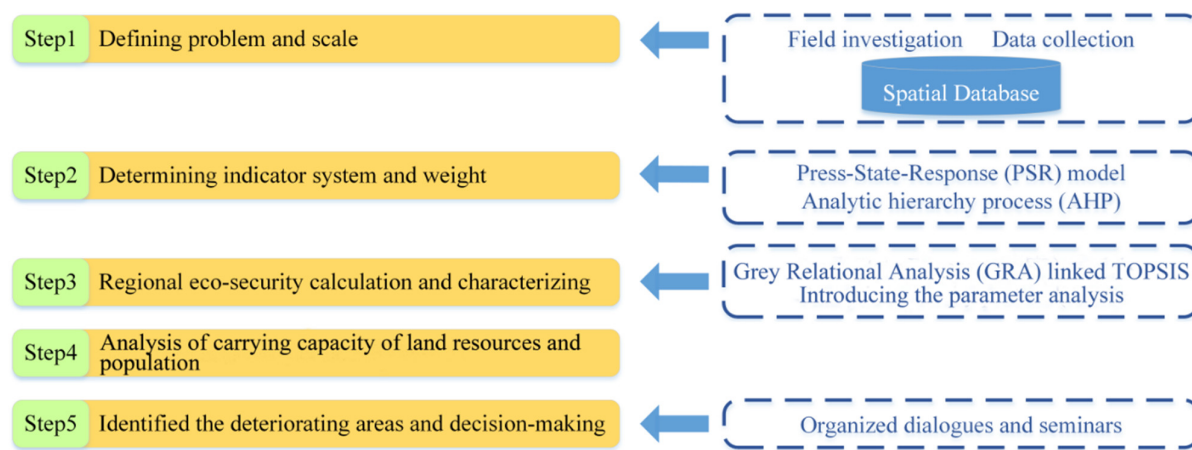


**Figure 2.** Procedure for regional land eco-security assessment in Daye.

*2.3. Conceptual Model and Indicator Weight*

2.3.1. Pressure–State–Response Model

The approach of PSR assessment employs a simple model and statistical criteria for indicator variables to determine the pressure, state, and response decision [46,47]. The three dimensions and two factors specific to that particular dimension were determined separately and were then integrated into a single rating [48,49]. Based on the PSR framework, an index system of regional land eco-security assessment was suggested with three dimensions, i.e., pressure, state, and response layer involving 18 relevant indicators, is shown in Table 1. These indicators were evaluated by a panel of experts from universities, officials, environmental organisations, landholders, and local residents to reflect the practical ecological situation of the Daye area on the regional scale. The pressure layer included four types of indicators, namely natural disaster, land use change, cumulative pollutant emission, and resource consumption, which indicate that the regional ecosystem was influenced by nature and anthropic factors. The state layer in-

cluded three types of indicators, namely environmental quality, ecological function, and landscape pattern, which represent the functional status of the regional ecosystem. Finally, the response layer included two types of indicators, namely the environment and policies, thus reflecting the degree of effective governance for the regional environment [50].

**Table 1.** Indicator system of regional land eco-security on the Daye area.

| System Layer | Type Layer | Indicator Layer | Data Description |
|---|---|---|---|
| Pressure | Nature disaster | Geological disaster | Hazard level |
| | Land use change | Urbanisation | Urbanisation intensity (%) |
| | | Lake-area reclamation | Intensity of water to farmland (%) |
| | | Mining | Hazard level |
| | Cumulative emission of pollutants | Industrial point source pollution | Load density of polluting enterprises (%) |
| | | Agricultural non-point source pollution | Applied load of crop area per hm² |
| | Resource consumption | Water consumption | Load of water consumption (10,000 ton/km²) |
| | | Consumption of biological resources | Total annual consumption (10,000 ton/km2) |
| State | Environmental quality | Soil quality | Soil organic matter content (%) |
| | | Soil heavy metal pollution | Nemerow composite index (%) |
| | | Water quality | Water pollution index (%) |
| | Ecological function | Ecological resilience (ER) | Landscape index |
| | | Ecological productivity | Net primary productivity (NPP) |
| | Landscape pattern | Landscape fragmentation | Landscape index |
| Response | Environmental response | Nature reserve | Nature reserves area (%) |
| | | Treatment of industrial sewage | Industrial wastewater complying with discharge standards (%) |
| | | Treatment of industrial solid waste | Utilised industrial solid waste (%) |
| | Policy response | Land consolidation | Increasing intensity of land reclamation (%) |

### 2.3.2. Analytical Hierarchy Process (AHP)

The AHP is particularly applicable for the evaluation of problems in which qualitative factors dominate [28,29]. This method has been widely applied to evaluate weights for the assessment of eco-security under the PSR framework. The weights between the security factors are calculated by comparing the relative importance between two factors at a time (two-by-two), and then aggregating them. This procedure is similar to those of previous studies using AHP. In this study, the weights were derived for each eco-security factor by the AHP method based on the relative importance of these indicators on regional ecological security as perceived by experts in the field (Table 2).

**Table 2.** Weight design of risk sources in the Daye area.

| Intensity of Importance | Land Eco-Security Factors | Weights |
|---|---|---|
| 1 | Mining | 0.178 |
| 2 | Urbanisation | 0.14864 |
| 3 | Geological disasters | 0.12357 |
| 4 | Lake-area reclamation | 0.10238 |
| 5 | Ecological resilience | 0.0846 |
| 6 | Soil heavy metal pollution | 0.06975 |
| 7 | Soil quality | 0.05741 |
| 8 | Industrial point source pollution | 0.04718 |

| 9 | Water quality | 0.03873 |
| 10 | Treatment of industrial sewage | 0.03178 |
| 11 | Agricultural non-point source pollution | 0.02608 |
| 12 | Treatment of industrial solid waste | 0.02142 |
| 13 | Ecological productivity | 0.01763 |
| 14 | Land consolidation | 0.01456 |
| 15 | Nature reserve | 0.0121 |
| 16 | Landscape fragmentation | 0.01014 |
| 17 | Water consumption | 0.0086 |
| 18 | Consumption of biological resources | 0.00742 |

*2.4. Data Collection and Processing*

A total of 18 indicators were included in our indicator system for regional eco-security. The data collection and processing were generally same as Guo et al. [26, 45]. In 2020, Volm 419 and 741 with modification.

The research team carried out a series of investigations on ecological-environment damage resulting from mining in the Daye area from 2013 to 2016. The studied sites included copper, iron, coal, gold, and silver mines, and related smelting sites, ore dressing sites, quarries, tailing reservoirs, coal gangue dumps, and open metal mines. The problems concerned over 800 different damages to the earth surface and vegetation, 349 geological hazards (e.g., collapse, gob areas, excavation, landslide, and water depletion), 550 land damages caused by solid-waste dumping, and 1294 land plaques covering an area of 6943.58 ha. The team conducted field investigation, plotting, and scene photography to obtain the information of each plot. A group of experts performed intra-industry interpretation, on-site verification, and hazard-level classification. Finally, the research team performed spatial processing based on the statistical information obtained for each plot.

The Environmental Protection Bureau of Daye City conducted interviews and survey, and provided the research team with water quality monitoring data, quarterly from 2016 to 2018. The levels of water quality degradation (i.e., heavy, moderate, or light pollution) were determined based on the above data, with ammonia–nitrogen content, eutrophication, and heavy metal pollution selected as criteria. GIS spatial processing was performed for the selected indices based on the geographical information of the sampled points.

Altogether, 225 valid samples were identified over the study area. The samples represented rural settlements, farmland, benchland, and irrigation districts in the surrounding industrial and mining areas, which are the major types of land use types in the Daye area. Soil quality was investigated based on the soil organic matter content.

The issue of heavy-metal pollution caused by mining and mineral processing has aroused interest of some local researchers [51–53]. They performed atomic absorption spectrophotometry to determine the levels of Cu, Pb, Hg, and Cd [54–56], barium chromate spectrophotometry to measure the As content [54,57], and applied the Nemerow index [58,59] to calculate the individual concentration of heavy metals (i.e., Cu, Pb, Cd, and As) so as to obtain the Nemerow composite index. The above data were processed as spatial data and integrated into a GIS.

Industrial point source pollution was determined according to the statistical point location distribution of polluting enterprises. The degree of influence of polluting enterprises within a certain range of each spatial position was calculated using the kernel density analysis method in GIS. The load density of polluting enterprises (number of enterprises/km$^2$) represented the pollution intensity of the point source.

In previous studies, landscape fragmentations resulting from road building, urban sprawl, and other artifacts of urban development had serious effects on the ecological security and life cycle of wildlife in the surrounding areas [60,61]. In our analysis, we

used FRAGSTATS 4.0 and generated a spatial distribution map of the patch density, and the fragmentation indicator was calculated using the following formula:

$$FI_i = \frac{N_i}{TA_i} \tag{1}$$

where $FI_i$ is the fragmentation indicator for a given sampling block $i$, $N_i$ is the number of the patches for all of the land use types in a given sampling block i, $TA_i$ is the total area of sampling block $i$.

Ecological resilience (ER) can be considered an attribute of landscape ecological stability [62,63]. Thus, we designed a gradation index system for eight major types of land cover that represented the factors of multiple land use policy involved in ER. The urban and rural residential areas were assigned a factor score of 0, 1, 3, 5, 7, 9, and 11 for least resilience, arable lands, gardens, grasslands, lakes and rivers, wetlands, and forests (highest resilience), respectively. We then generated a spatial distribution map of the ER, and calculated it with the following formula:

$$ER_i = \sum_{j=1}^{n} \frac{a_{ij}M_j}{TA_i} \tag{2}$$

where $ER_i$ represented the ER of a given sampling block $i$, $a_{ij}$ represented the area of land use type j in each sampling block $i$, $M_j$ represented the grade of resilience for land use type $j$, $TA_i$ represented the total area of sampling block $i$, and n represented the number of land use types.

The net primary productivity (NPP) data were obtained from the photosynthetic effective radiation and utilisation rate of light energy using a conceptual model based on remote sensing and GIS technology. In ArcGIS 10.2, the NPP data were graded and assigned following the standardised grading method for representing the situation of primary productivity of each township in the Daye area.

Based on the remote sensing interpretation data, we extracted 5 nature reserves, i.e., 290.4 km$^2$ in the Baoan lake wetland reserve, 55 km$^2$ in the Leishan forest reserve, 18 km$^2$ in the Daguangou forest reserve, 62 km$^2$ in the Dongjiakou forest reserve, and 87 km$^2$ in the Huangshan Forest Reserve.

Based on the 2018 land use maps of the Daye area, we performed the data application of the land use category. We obtained a large quantity of data from the Daye Statistical Yearbook (2018) and from surveys on such topics as the consumption of water resources and biological resources, application of pesticides and fertilisers, treatment of industrial sewage and solid waste, SO$_2$ emissions, and land consolidation areas. All of the above processes were performed using ArcGIS 10.2.

### 2.5. Eco-Security Index Calculation

We evaluated the ecological security on a regional scale by considering the characteristics of our established index system involving ecology, economy, society, and technology. Based on the TOPSIS combined GRA approach, we calculated the spatial ecological security index (ESI) on a regional scale. The process used was as follows. First, three components (pressure, state, and response) were treated using attribute assimilation and the data were normalised. Second, the positive ideal solutions (best) and negative ideal solutions (worst) were determined by the TOPSIS [30,31]. The positive ideal solution $r^+$, which represents the best eco-security status, and the negative ideal solution, $r^-$, which represents the worst eco-security status, were determined as follows:

$$r^+ = \left\{ \left( \max_{1 \le i \le m} r_{ij} \, \Big| \, j \in J^+ \right), \left( \min_{1 \le i \le m} r_{ij} \, \Big| \, j \in J^- \right) \right\} = (r_1^+, r_2^+, \cdots, r_n^+) \tag{3}$$

$$r^- = \left\{ \left( \min_{1 \le i \le m} r_{ij} \, \Big| \, j \in J^+ \right), \left( \max_{1 \le i \le m} r_{ij} \, \Big| \, j \in J^- \right) \right\} = (r_1^-, r_2^-, \cdots, r_n^-) \tag{4}$$

where $J^+$ and $J^-$ are the sets of positive (+) and negative (−) indices, respectively.

The distance between each alternative and the positive ideal solution ($l_i^+$)or negative ideal solution ($l_i^-$) were calculated as follows:

$$l_i^+ = \sqrt{\sum_{j=1}^{n}\left[\left(r_{ij} - r_j^+\right)^2\right]}, 1 \leq i \leq m, 1 \leq j| \leq n \tag{5}$$

$$l_i^- = \sqrt{\sum_{j=1}^{n}\left[\left(r_{ij} - r_j^-\right)^2\right]}, 1 \leq i \leq m, 1 \leq j \leq n \tag{6}$$

where $l_i^+(l_i^-)$ is the Euclidean distance, and the distance shows if the evaluation unit is closer to the best or worst eco-security status.

The grey relational coefficients between the ESI were calculated under the PSR framework and the positive and negative ideal solutions. The grey relational coefficient reflects the degree of closeness between the two sequences [35,37,38]. The grey relational coefficient $q_{ij}$ of a grey model with the positive or negative ideal is calculated as shown in Equations (7) and (8), respectively.

$$q_{ij}^+ = \frac{\min_i \min_j \left|r^+ - r_{ij}\right| + \varepsilon \max_i \max_j \left|r^+ - r_{ij}\right|}{\left|r^+ - r_{ij}\right| + \varepsilon \max_i \max_j \left|r^+ - r_{ij}\right|} \tag{7}$$

$$q_{ij}^- = \frac{\min_i \min_j \left|r^- - r_{ij}\right| + \varepsilon \max_i \max_j \left|r^- - r_{ij}\right|}{\left|r^- - r_{ij}\right| + \varepsilon \max_i \max_j \left|r^- - r_{ij}\right|} \tag{8}$$

where $r^+$ and $r^-$ are the positive (+) and negative (−) ideal solution, respectively. $\varepsilon$ is the distinguishing coefficient, and $\varepsilon \epsilon |0, 1|$. $\varepsilon = 0.5$ is normally applied following the rule of the least information. Subsequently, the grey relational coefficient matrices $Q^+ = (q_{ij}^+)_{m*n}$ and $Q^- = (q_{ij}^-)_{m*n}$ are obtained.

The grey relational degree between evaluation unit $i$ and positive and negative ideal solutions is calculated as shown in Equations (9) and (10), respectively.

$$q_i^+ = \frac{1}{n}\sum_{j=1}^{n} q_{ij}^+, \quad 1 \leq i \leq m \tag{9}$$

$$q_i^- = \frac{1}{n}\sum_{j=1}^{n} q_{ij}^-, \quad 1 \leq i \leq m \tag{10}$$

where $q_i^+(q_i^-)$ is the grey relational degree, which indicates if the evaluation unit is closer to the best (worst) eco-security status and if the eco-security level of the area is higher (lower).

The results of the dimensionless distance and dimensionless grey relational degree were integrated as follows.

$$S_i^+ = \alpha L_i^+ + \beta Q_i^+, \quad 1 \leq i \leq m \tag{11}$$

$$S_i^- = \alpha L_i^- + \beta Q_i^-, \quad 1 \leq i \leq m \tag{12}$$

where $S_i^+(S_i^-)$ denotes the comprehensive relation between the evaluation unit (area) A_i and the positive (negative) ideal solution. $L$ represents the normalized value of the Euclidean distance, $Q$ represents the normalized value of the correlation coefficient. The normalized formula is:

$$OG_i = \frac{OG_i}{\max\limits_{1 \le i \le m} OG_i}, \quad i = 1,2,\dots,m$$

$OG_i$ includes Euclidean distance and Grey relational degree.

In addition, $\alpha + \beta = 1, \alpha > 0, \beta > 0$, where $\alpha$ and $\beta$ reflect the degree of subjective preferences of decision makers, which are entirely dependent on them. The current Grey–TOPSIS algorithm fails to further consider the values taken by $\alpha$ and $\beta$, leading to a certain level of subjectivity in parametric values across most studies. On this basis, we further examined the values taken by $\alpha$ and $\beta$. Specifically, calculations were conducted using 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9 for $\alpha$ and 0.9, 0.8, 0.7, 0.6, 0.5, 0.4, 0.3, 0.2, 0.1 for $\beta$. Land eco-security of Daye City under different values of $\alpha$ and $\beta$ was obtained, and eco-security spatial distributions that were most relevant to factual conditions were selected. The modified parametric design was introduced to reduce human subjectivity, thereby increasing the practicality and accuracy of the results.

The relative closeness $c_i^+$ of evaluation unit (area) $A_i = (i = 1, 2, \cdots m)$ was calculated as follows.

$$c_i^+ = \frac{S_i^+}{S_i^- + S_i^+}, \quad 1 \le i \le m \tag{13}$$

A higher relative closeness $c_i^+$ implies that the evaluation unit $A_i$ is close to the (best) positive ideal solution and far away from the (worst) negative ideal solution. This means that the eco-security level of $A_i$ is higher. Thus, each evaluated area can be compared with the best and worst eco-security statuses to acquire its relative closeness; thus, this indicator can be used to rank the sustainability level of cities. Therefore, it can be used to classify the different levels of eco-security on a regional scale.

The results were ranked according to the relative closeness $c_i^+$. Subsequently, the regional ESI levels for eco-security areas were classified as very low, low, moderate, high, and very high. The spatial visualisation of the results can be used by decision makers to manage regional ecological protection.

### 2.6. Carrying Capacity Analysis under Regional Eco-Security

Urban development must be pursued without destroying the balance and virtuous cycle of ecological systems [64]. Therefore, determining the scale of a secure urban ecological land use and the population carrying capacity underpinned by such ecological security is of great significance for the development of Daye City. For that, the study area was divided into six sub-regions based on their functional division of mining cities, ecological, and geographical features.

#### 2.6.1. Carrying Capacity Analysis of Land Resources

Analysis of land carrying capacity in the context of ecological security helps reveal the ecological characteristics of land under human activities from a land-use perspective, thereby providing an important basis for the reasonable development of regional land resources [64,65]. We utilised a spatial overlay approach to analyse the present-day land use and evaluation results of ecological security (using geological boundaries of extremely high, high, medium, low, and extremely low security zones). The area and proportion in relation to land use types of each sub-region under different ecological security conditions were extracted to analyse their spatial layout features, and suggestions were proposed for subsequent spatial adjustments.

#### 2.6.2. Carrying Capacity Analysis of Population

Population growth exerts a crucial influence on the regional environmental capacity and sustainability of resources [66]. Therefore, the population carrying capacity under the constraint of ecological security is a great reference for urban development planning.

Requirements on land use for urban construction cover aspects of living space, transport, greenisation, and everyday life to fulfil human subsistence and development [67,68].

Based on previous studies, we identified the entire extremely low security zone, 20% of the low security zone, and 60% of the medium security zone as falling into the category of ecologically constrained land use based on ecological security evaluations [69,70]. As such, the land that can be used for urban construction covers 40% of the medium security zone and 80% of the high and extremely high security zones. On this basis, the area of land used for urban construction in each sub-region can be calculated. Additionally, the population that can be supported by six sub-regions can be calculated against the present-day criterion of 110 m² per urban resident in China [71,72]. Together, these data reflect the characteristics of land resources and the population carrying capacity of each sub-region.

## 3. Results

### 3.1. Numeral Calculation and Spatial Distribution of Land Eco-Security

Based on the modified Grey–TOPSIS, regional land eco-security was calculated for the Daye area. The positive and negative ideal solutions of Euclidean distance and grey relational degree for each pixel were calculated in a GIS environment (Table 3). The closeness degree was also evaluated under different parameter designs ($\alpha$ and $\beta$) (Table 4). Figure 3 shows the spatial distribution of regional land eco-security under different parameter designs in the Daye area. Combined with the field survey in Daye (real nature, economy, and environment), the research team selected the spatial distribution closest to the actual situation (when the parameter design is $\alpha = 0.9$, $\beta = 0.1$) for subsequent analysis.

**Table 3.** Positive and negative ideal solutions for Euclidean distance and Grey relational degree.

| Plot Numbers | *D* + | *D* − | *R* + | *R* − |
|---|---|---|---|---|
| FK001 | 0.00125725 | 0.02352097 | 0.820823354 | 0.406491266 |
| FK002 | 0.001102489 | 0.023526267 | 0.822042596 | 0.396503794 |
| FK003 | 0.001163902 | 0.023525039 | 0.816829911 | 0.411037236 |
| FK004 | 0.001106563 | 0.023524801 | 0.791765184 | 0.414904255 |
| ... | ... | ... | ... | ... |

Plot numbers: each grid in GIS processing; *D*+: positive Euclidean distance; *D*-: negative Euclidean distance; *R*+: positive ideal solution of Grey relational degree; *R*-: negative ideal solution of Grey relational degree.

The very low and low security areas were mainly distributed in three regions: the urban centre in the northeast, iron mining area in the northwest, and copper mining area in the east. The moderate security areas were scattered across middle and southern regions and mainly included towns and rural settlements. The high security areas were located in the middle-east and southern Daye area, mostly including arable lands and forests. The very high security areas were mainly limited to the southern and north-western regions, including most of the mountainous and wetland reserves. These findings were confirmed by our study group focused on field observation.
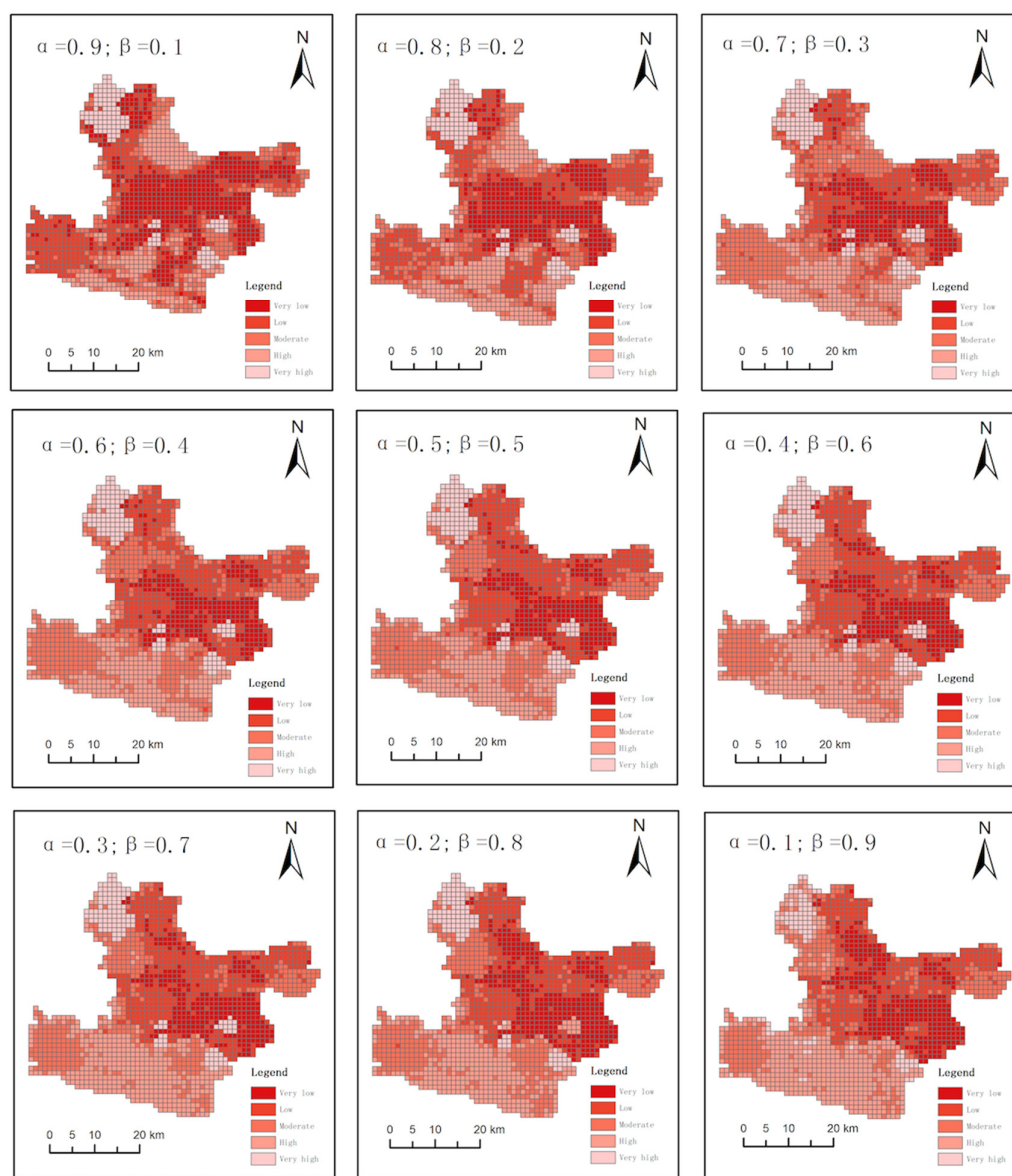
**Figure 3.** Map of regional land eco-security distribution on Daye. The ESI is classified as: very low (< 0.101), low (0.101 < ESI < 0.112), moderate (0.112 < ESI < 0.125), high (0.125 < ESI < 0.151), and very high (> 0.151).

Percentage areas were calculated using the ESI level grid cell numbers multiplied by the grid cell size of 1 × 1 km. Very low eco-security classes comprised 5.65% (87.68 km²) of the total area, highlighting the serious deterioration of ecosystems in some areas on Daye. Low security areas accounted for 18.20% (285.02 km²) of the total area, moderate security areas for 31.64% (494.50 km²), and high and very high security areas for 27.25% (426.73 km²) and 17.30% (271.12 km²), respectively.
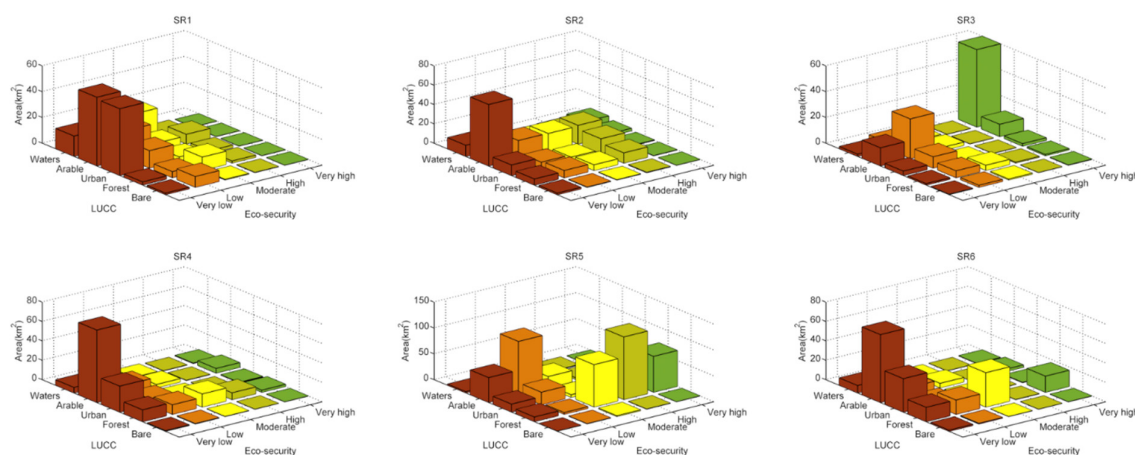
### 3.2. Analysis of Land Carrying Capacity in the Context of Ecological Security

The resource supporting capacity of each sub-region of Daye City under the constraint of ecological land use is shown in Figure 4. In sub-region 1, a large amount of urban and farmland, accounting for 51.76 and 53.25 km², respectively, is in an extremely unsecured state. In sub-region 2, 12.63 and 14.36 km² of farmland and bare land, respec-

tively, are in extremely low security state. In sub-region 3, a considerable proportion of the water area, reaching 60.07 km², is in highly secure ecological conditions. In sub-region 4, land use in extremely insecure conditions mainly involves farm and urban land, accounting for 74.71 and 32.83 km², respectively. In sub-region 5, most of the forest area, accounting for 142.35 km², is in an extremely high or high security state. Nonetheless, 103.74 km² of farmland is in a low security state. In sub-region 6, most farmland, urban land, and water areas are at an extremely low security state, accounting for 70, 37.67, and 9.46 km², respectively.

**Table 4.** Closeness degree under different parameters.

| Plot Numbers | a = 0.9; β = 0.1 | a = 0.8; β = 0.2 | a = 0.7; β = 0.3 | a = 0.6; β = 0.4 | a = 0.5; β = 0.5 | a = 0.4; β = 0.6 | a = 0.3; β = 0.7 | a = 0.2; β = 0.8 | a = 0.1; β = 0.9 |
|---|---|---|---|---|---|---|---|---|---|
| FK001 | 0.521 | 0.486 | 0.449 | 0.408 | 0.363 | 0.313 | 0.258 | 0.197 | 0.128 |
| FK002 | 0.527 | 0.491 | 0.452 | 0.410 | 0.364 | 0.313 | 0.257 | 0.194 | 0.124 |
| FK003 | 0.517 | 0.483 | 0.445 | 0.405 | 0.36 | 0.31 | 0.255 | 0.194 | 0.125 |
| FK004 | 0.507 | 0.473 | 0.436 | 0.396 | 0.351 | 0.302 | 0.248 | 0.188 | 0.121 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |



**Figure 4.** Carrying capacity of land resources under the ecological constraint for each sub-region in Daye.

### 3.3. Analysis of Population Carrying Capacity in the Context of Ecological Security

The population carrying capacity of each sub-region of Daye City under the constraint of ecological land use is shown in Figure 5. The population carrying capacities of land in sub-regions 1–6 are 237,000, 705,600, 689,200, 224,500, 1,440,600, and 337,100, respectively. Distinct regional differences can be observed when comparing the factual population sizes and gross domestic product (GDP). The upper limit for population carrying capacity is exceeded in sub-region 1; population carrying capacities in sub-regions 4 and 6 are on par with their actual population sizes; and sub-regions 2, 3, and 5 have considerable room left in terms of their population carrying capacities.
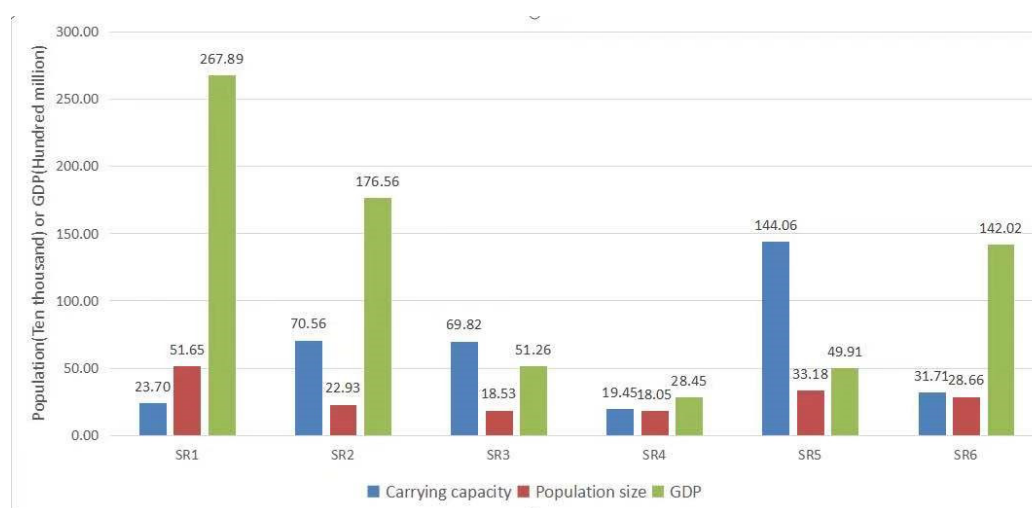
**Figure 5.** Population carrying capacity under the constraint of ecological land use for each sub-region in Daye City.

## 4. Discussion

The assessment results reveal the characteristics of the land eco-security and its ability to assist in the decision-making process to determine the most efficient actions with key implications for ecological protection.

### 4.1. Implications for Regional Eco-Security Management on Daye

This study shows the eco-security characteristics of the entire ecosystem in the Daye area and the implications for ecological management in the area.

In the very low eco-security part of the area, regulations for careful mining planning are suggested for the local government to minimise the destruction of the earth's surface. Moreover, measures for immediate remediation of the damaged soil should be defined. Investments are recommended to fill-in gobs, and measures to solve the problem of ecological refugees are to be taken when necessary. Another main problem is the large areas with soil heavy metal pollution. The recovery mechanism of heavy metal pollution in soils is extremely complex and costly. Therefore, the government needs to design long-term and effective recovery projects.

In the low eco-security area, urban construction areas should be carefully and scientifically planned to occupy the smallest possible amount of arable land and to preserve as much water and forests as possible. Moreover, this area should be prioritised for emission control, pollutant treatment, and more significantly, clean industrial production.

In the medium eco-security part, we suggested strict rules and regulations for scientific and rational aquaculture, in which water quality monitoring is an important preventive measure, and the application of organic feed should be promoted in lake areas. In addition, farmers should be informed and encouraged to adopt organic fertilisers instead of chemical ones, grow disease-and-pest-resistant crops, and leave land fallowed regularly.

In the high eco-security part of the area, we suggest measures for ecosystem protection including establishment of alternative sources of economic income for the residents in the forest areas and limitation of the access of herders to grazing by instructing them of the benefit of rational grazing. A large area of water and wetland in the northwest was proposed to be improved into an ecological demonstration area. Meanwhile, we are committed to applying for a national wetland park to protect this important habitat for a long time.

Finally, due to the complexity of regional ecosystems, having both emergency and long-term goals is necessary in ecological security decision planning.

*4.2. Implications for Carrying Capacity of Land Resources and Population*

In its urbanisation process, sub-region 1, as the economic centre of the Daye area, has experienced a massive industrial clustering process. Expansion in the urban scale has caused a factual population to far exceed the limited carrying capacity of the land there. Additionally, a continuously overheated economy has led to a significant deficiency in land resource reserves. Thus, we propose that more towns should be established and the scale of construction land use be expanded in sub-regions 2 and 3.

Long-term mining activities have caused massive waste and abandonment of farmland in sub-region 2 (a traditional iron ore mining zone). A considerable proportion of residential areas around the mining field is no longer suitable for living. Thus, the government should promptly allocate new land and coordinate with the relocation of high-risk residential areas.

Sub-region 3 boasts well-preserved water areas that have been incorporated into the construction of a national wetland park. Given the abundant wetland and water area resources in the sub-region, land planning priorities should include tourism and real estate development, which not only attracts inflows of massive urban populations, but also alleviates the population carrying pressure felt by the industrial development zone. In addition, the sub-region is estimated to achieve a GDP of more than CNY 10 billion in the forthcoming plan period.

In sub-region 4, a large proportion of urban land use is currently in an extremely low security state. Particular attention should be paid to ecological improvement in the mineral processing belt through measures such as emission control, technological innovation, and financial support. With an improved ecological environment in the future, large areas of land dedicated to industrial development should be allocated to relieve land use requirements from sub-region 1. In the meantime, transportation advantages should be sufficiently leveraged to boost economic benefits generated by the mineral processing industry.

Ecological resources in the southern forestry of sub-region 5 have been well protected; thanks to the governmental implementation of the policy of returning farmland to forestry. Forest resources, which account for nearly 433 km$^2$, represent an integral part of the ecosystem functionality of Daye City. Despite its massive potential for population carrying capacity, the sub-region has seen a rather slow urbanisation process due to a low GDP scale. Governmental attention should be paid to local resident employment and economic conditions. It is advisable that land zoned for industrial use should be appropriately expanded to introduce new industries, such as agricultural and food processing, which would relieve employment pressures and labour losses. In the meantime, subsidies for forest planting should be provided, or peasants should be guided to transit towards other economic development modes.

In sub-region 6, heavy metal pollution from copper mining has resulted in massively stagnated land resource development in north, which requires ecological restoration. However, the complexity, long duration, and high cost associated with the restoration of soil heavy-metal pollution means that governmental administrators must design a long-term plan for land reclamation and restoration. Given the strong fiscal revenues from copper mining, it is feasible to relocate industrial areas southwards and construct new residential areas in a step-wise manner to relieve the population carrying pressure on land.

*4.3. Implications for Regional Eco-Security Modelling Assessment*

TOPSIS linked GRA was applied in the modelling to support the assessment of ecological security, thus reflecting the flexibility of decision-making tools on a regional

scale. A major contribution of this paper is the introduction of a parameter design to reduce the subjectivity of the Grey–TOPSIS method and obtain more practical results. The multi-factor investigation employed in the present study is also useful for comprehensive evaluation of an entire land ecosystem. Appropriate decision-making depends on conducting a complete analysis of the degraded ecosystem on a regional scale. Our application of a traditional mining city has demonstrated the eco-security methodology capabilities and its flexibility in addressing the need for regional environmental protection.

However, different types of data come from experts with different backgrounds, which is difficult to be quantified and spatialized later. Therefore, we should pay more attention to the normalization step of the various data in the modelling process, because normalization of the processing method as a key technique should be improved based on more wisdom in current the multi-criteria decision analysis (MCDA) methods [31,73].

The capability GIS was used to visualise the different levels of eco-security on a larger scale, and the spatial visualization expression was widely accepted by various local participants. This still requires further development of the combined application of MCDA and GIS in the future [74]. For example, we will develop spatiotemporal modelling of systematic dynamics in the field of ecological security on large-scale investigation [1,75].

Most approaches were aimed at seeking the decision tools for large-scale eco-security to obtain the environmentally safe, localized, and economically profitable strategies [76,77]. Regional eco-security assessment not only identifies where the most urgent need is for remediation, but also helps to reveal the ecological mechanisms of land degradation. At the same time, we should also be concerned that popularization of the TOPSIS technology and sharing of the software would be helpful for land planners to master the technology. In addition, many studies rely too much on quantitative modelling calculations, and the results cannot be generally accepted. Therefore, encouragement of participation by different stakeholders of local land resources is proposed so that decision-making will be widely accepted [78,79].

## 5. Conclusions

In this study, we conducted a land eco-security assessment on a regional scale by incorporating the PSR framework, GIS-based TOPSIS, and GRA, and applied it to the traditional mining city of Daye city. The results show the spatial security patterns of the entire ecosystem, and priority options for various stakeholders are provided. An analysis of the carrying capacity of land resources and population for each sub-region was presented, and sustainable urban planning options were defined. This spatial decision-support tool would be practical for ecological protection and resource sustainable management. However, the strategies of policy-makers derived from our model need to be evaluated and confirmed in practice for ecological management. Moreover, the present model and method should be further evaluated for its validity using other regional ecosystems to determine the scope of its applicability. We will continue to modify our decision-making tools which are of guiding significance for researchers in land resource and environmental management. For example, with the maturity of the GIS–TOPSIS technology, it is expected to develop software and popularize it in land planners. We also need to develop the nonlinear design to reduce the uncertainty concerning model calculation, and to develop a new approach to check the accuracy of model simulations [25,80]. Systematic and dynamic modelling is also very consistent with the simulation of ecosystem processes. In the future, we will develop spatiotemporal modelling of systematic dynamics in the field of ecological degradation on large-scale investigation.

**Author Contributions:** Conceptualization, K.G., X.Z.,and Y.C.; methodology, K.G., M.C. and Y.L. (Yi Liu); software, M.C., Y.L. (Yang Liu) and H.W.; validation, W.C., Y.L. (Yi Liu), and Z.C.; formal analysis, M.C., X.Z., jianguo zhang, W.C. and Z.C.; investigation, K.G., M.C., Y.C., Y.L. (Yi Liu),

# References

1. Wu, X.; Liu, S.L.; Sun, Y.X.; An, Y.; Dong, S.K.; Liu, G.H. Ecological security evaluation based on entropy matter-element model: A case study of Kunming city, southwest China. *Ecol. Indic.* **2019**, *102*, 469–478.
2. Wu, K.Y.; Ye, X.Y.; Qi, Z.F.; Zhang, H. Impacts of land use/land cover change and socioeconomic development on regional ecosystem services: The case of fast-growing Hangzhou metropolitan area, China. *Cities* **2013**, *31*, 276–284.
3. Peng, J.; Zhao, M.Y.; Guo, X.N.; Pan, Y.J.; Liu, Y.X. Spatial-temporal dynamics and associated driving forces of urban ecological land: A case study in Shenzhen City, China. *Habitat Int.* **2017**, *60*, 81–90.
4. Fahrig, L.; Arroyo-Rodriguez, V.; Bennett, J.R.; Boucher-Lalonde, V.; Cazetta, E.; Currie, D.J.; Eigenbrod, F.; Ford, A.T.; Harrison, S.P.; Jaeger, J.A.G.; et al. Is habitat fragmentation bad for biodiversity? *Biol. Conserv.* **2019**, *230*, 179–186.
5. Cielemecka, O. Forest futures: Biopolitics, purity, and extinction in Europe's last 'pristine' forest. *J. Gend. Stud.* **2020**, *29*, 63–75.
6. Yu, D.; Wang, D.Y.; Li, W.B.; Liu, S.H.; Zhu, Y.L.; Wu, W.J.; Zhou, Y.H. Decreased Landscape Ecological Security of Peri-Urban Cultivated Land Following Rapid Urbanization: An Impediment to Sustainable Agriculture. *Sustainability* **2018**, *10*, 394.
7. Hazbavi, Z.; Sadeghi, S.H.; Gholamalifard, M.; Davudirad, A.A. Watershed health assessment using the pressure-state-response (PSR) framework. *Land Degrad. Dev.* **2020**, *31*, 3–19.
8. Maanan, M.; Maanan, M.; Rueff, H.; Adouk, N.; Zourarah, B.; Rhinane, H. Assess the human and environmental vulnerability for coastal hazard by using a multi-criteria decision analysis. *Hum. Ecol. Risk Assess.* **2018**, *24*, 1642–1658.
9. Li, F.Z.; Guo, S.Y.; Li, D.; Li, X.; Li, J.; Xie, S. A multi-criteria spatial approach for mapping urban ecosystem services demand. *Ecol. Indic.* **2020**, *112*, 106119.
10. Xie, H.L.; He, Y.F.; Choi, Y.; Chen, Q.R.; Cheng, H. Warning of negative effects of land-use changes on ecological security based on GIS. *Sci. Total Environ.* **2020**, *704*, 135427.
11. Mallick, J.; Singh, R.K.; AlAwadh, M.A.; Islam, S.; Khan, R.A.; Qureshi, M.N. GIS-based landslide susceptibility evaluation using fuzzy-AHP multi-criteria decision-making techniques in the Abha Watershed, Saudi Arabia. *Environ. Earth Sci.* **2018**, *77*, 276.
12. Guo, K.; Kuai, X.; Chen, Y.Y.; Qi, L.; Zhang, L.; Liu, Y.F. Risk assessment of land ecology on a regional scale: Application of the relative risk model to the mining city of Daye, China. *Hum. Ecol. Risk Assess.* **2017**, *23*, 550–574.
13. Xu, X.B.; Yang, G.S.; Tan, Y. Identifying ecological red lines in China's Yangtze River Economic Belt: A regional approach. *Ecol. Indic.* **2019**, *96*, 635–646.
14. Liu, Z.F.; He, C.Y.; Yang, Y.J.; Fang, Z.H. Planning sustainable urban landscape under the stress of climate change in the drylands of northern China: A scenario analysis based on LUSD-urban model. *J. Clean. Prod.* **2020**, *244*, 118709.
15. Peng, J.; Yang, Y.; Liu, Y.X.; Hu, Y.N.; Du, Y.Y.; Meersmans, J.; Qiu, S.J. Linking ecosystem services and circuit theory to identify ecological security patterns. *Sci. Total Environ.* **2018**, *644*, 781–790.
16. Feng, Y.J.; Yang, Q.Q.; Tong, X.H.; Chen, L.J. Evaluating land ecological security and examining its relationships with driving factors using GIS and generalized additive model. *Sci. Total Environ.* **2018**, *633*, 1469–1479.
17. Sun, Z.G.; Sun, W.G.; Tong, C.; Zeng, C.S.; Yu, X.; Mou, X.J. China's coastal wetlands: Conservation history, implementation efforts, existing issues and strategies for future improvement. *Environ. Int.* **2015**, *79*, 25–41.
18. Feng, Y.J.; Liu, Y.; Liu, Y. Spatially explicit assessment of land ecological security with spatial variables and logistic regression modeling in Shanghai, China. *Stoch. Environ. Res. Risk Assess.* **2017**, *31*, 2235–2249.
19. Goddard, M.A.; Dougill, A.J.; Benton, T.G. Scaling up from gardens: Biodiversity conservation in urban environments. *Trends Ecol. Evol.* **2010**, *25*, 90–98.

20. Kong, F.H.; Yin, H.W.; Nakagoshi, N.; Zong, Y.G. Urban green space network development for biodiversity conservation: Identification based on graph theory and gravity modeling. *Landsc. Urban Plan.* **2010**, *95*, 16–27.

21. Wang, Z.H.; Yang, L.; Yin, J.H.; Zhang, B. Assessment and prediction of environmental sustainability in China based on a modified ecological footprint model. *Resour. Conserv. Recycl.* **2018**, *132*, 301–313.

22. Zhang, J.T.; Zhang, Y.Q.; Qin, S.G.; Wu, B.; Ding, G.D.; Wu, X.Q.; Gao, Y.; Zhu, Y.K. Carrying capacity for vegetation across northern China drylands. *Sci. Total Environ.* **2020**, *710*, 136391.

23. Su, Y.X.; Chen, X.Z.; Liao, J.S.; Zhang, H.O.; Wang, C.J.; Ye, Y.Y.; Wang, Y. Modeling the optimal ecological security pattern for guiding the urban constructed land expansions. *Urban For. Urban Green.* **2016**, *19*, 35–46.

24. Li, S.C.; Xiao, W.; Zhao, Y.L.; Xu, J.F.; Da, H.Z.; Lv, X.J. Quantitative Analysis of the Ecological Security Pattern for Regional Sustainable Development: Case Study of Chaohu Basin in Eastern China. *J. Urban Plan. Dev.* **2019**, *145*, 508.

25. Sałabun, W.; Urbaniak, K. *A New Coefficient of Rankings Similarity in Decision-Making Problems*; Springer International Publishing: Cham, Switzerland, 2020; pp. 632–645.

26. Guo, K.; Zhang, X.; Liu, J.; Wu, Z.; Chen, M.; Zhang, K.; Chen, Y. Establishment of an integrated decision-making method for planning the ecological restoration of terrestrial ecosystems. *Sci. Total Environ.* **2020**, *741*, 139852.

27. Nyimbili, P.H.; Erden, T.; Karaman, H. Integration of GIS, AHP and TOPSIS for earthquake hazard analysis. *Nat. Hazards* **2018**, *92*, 1523–1546.

28. Arabameri, A.; Rezaei, K.; Cerda, A.; Lombardo, L.; Rodrigo-Comino, J. GIS-based groundwater potential mapping in Shahroud plain, Iran. A comparison among statistical (bivariate and multivariate), data mining and MCDM approaches. *Sci. Total Environ.* **2019**, *658*, 160–177.

29. Arabameri, A.; Rezaei, K.; Cerda, A.; Conoscenti, C.; Kalantari, Z. A comparison of statistical methods and multi-criteria decision making to map flood hazard susceptibility in Northern Iran. *Sci. Total Environ.* **2019**, *660*, 443–458.

30. Kumar, A.; Sah, B.; Singh, A.R.; Deng, Y.; He, X.N.; Kumar, P.; Bansal, R.C. A review of multi criteria decision making (MCDM) towards sustainable renewable energy development. *Renew. Sustain. Energy Rev.* **2017**, *69*, 596–609.

31. Peng, X.D.; Selvachandran, G. Pythagorean fuzzy set: State of the art and future directions. *Artif. Intell. Rev.* **2019**, *52*, 1873–1927.

32. Sun, L.Y.; Miao, C.L.; Yang, L. Ecological-economic efficiency evaluation of green technology innovation in strategic emerging industries based on entropy weighted TOPSIS method. *Ecol. Indic.* **2017**, *73*, 554–558.

33. Meshram, S.G.; Alvandi, E.; Meshram, C.; Kahya, E.; Al-Quraishi, A.M.F. Application of SAW and TOPSIS in Prioritizing Watersheds. *Water Resour. Manag.* **2020**, *34*, 715–732.

34. Wang, T.D.; Wang, J.J.; Peng, D.H. Enterprise Quality Credit Evaluation Based on Grey Correlation Analysis and TOPSIS Method. In Proceedings of the 2014 International Conference on e-Education, e-Business and Information Management, Shanghai, China,17–19 April 2014; Volume 91, pp. 158–161.

35. Jiang, Y.X.; Liu, Y.S.; Ying, G.G.; Wang, H.W.; Liang, Y.Q.; Chen, X.W. A new tool for assessing sediment quality based on the Weight of Evidence approach and grey TOPSIS. *Sci. Total Environ.* **2015**, *537*, 369–376.

36. Lu, D.B.; Xu, J.H.; Yang, D.Y.; Zhao, J.A. Spatio-temporal variation and influence factors of PM2.5 concentrations in China from 1998 to 2014. *Atmos. Pollut. Res.* **2017**, *8*, 1151–1159.

37. He, D.; Yi, G.H.; Zhang, T.B.; Miao, J.Q.; Li, J.J.; Bie, X.J. Temporal and Spatial Characteristics of EVI and Its Response to Climatic Factors in Recent 16 years Based on Grey Relational Analysis in Inner Mongolia Autonomous Region, China. *Remote Sens.* **2018**, *10*, 961.

38. Tang, J.; Zhu, H.L.; Liu, Z.; Jia, F.; Zheng, X.X. Urban Sustainability Evaluation under the Modified TOPSIS Based on Grey Relational Analysis. *Int. J. Environ. Res. Public Health* **2019**, *16*, 256.

39. Nie, R.X.; Tian, Z.P.; Wang, J.Q.; Zhang, H.Y.; Wang, T.L. Water security sustainability evaluation: Applying a multistage decision support framework in industrial region. *J. Clean. Prod.* **2018**, *196*, 1681–1704.

40. Banaeian, N.; Mobli, H.; Fahimnia, B.; Nielsen, I.E.; Omid, M. Green supplier selection using fuzzy group decision making methods: A case study from the agri-food industry. *Comput. Oper. Res.* **2018**, *89*, 337–347.

41. Li, J.F.; Gu, A.L.; Ma, Z.Y.; Zhang, C.L.; Sun, Z.Q. Economic development, energy demand, and carbon emission prospects of China's provinces during the 14th Five-Year Plan period: Application of CMRCGE model. *Adv. Clim. Chang. Res.* **2019**, *10*, 165–173.

42. Liu, J.L.; Wang, K.; Zou, J.; Kong, Y. The implications of coal consumption in the power sector for China's $CO_2$ peaking target. *Appl. Energ.* **2019**, *253*, 113518.

43. Zhang, H.M.; Xiong, L.F.; Li, L.S.; Zhang, S.F. Political incentives, transformation efficiency and resource-exhausted cities. *J. Clean. Prod.* **2018**, *196*, 1418–1428.

44. Guo, S.S.; Zhang, Y.F.; Qian, X.Y.; Ming, Z.; Nie, R. Urbanization and $CO_2$ emissions in resource-exhausted cities: Evidence from Xuzhou city, China. *Nat. Hazards* **2019**, *99*, 807–826.

45. Guo, K.; Zhang, X.C.; Kuai, X.; Wu, Z.F.; Chen, Y.Y.; Liu, Y. A spatial bayesian-network approach as a decision-making tool for ecological-risk prevention in land ecosystems. *Ecol. Model.* **2020**, *419*, 108929.

46. Sun, T.T.; Lin, W.P.; Chen, G.S.; Guo, P.P.; Zeng, Y. Wetland ecosystem health assessment through integrating remote sensing and inventory data with an assessment model for the Hangzhou Bay, China. *Sci. Total Environ.* **2016**, *566*, 627–640.

47. May, N.; Guenther, E.; Haller, P. Environmental Indicators for the Evaluation of Wood Products in Consideration of Site-Dependent Aspects: A Review and Integrated Approach. *Sustainability* **2017**, *9*, 1897.

48. Zhang, C.; Li, Y.F.; Xiong, S.; Lu, X.W.; Zhu, X.D. Regional environmental risk assessment and management guide for rapid urbanization process of a city cluster in China. *Hum. Ecol. Risk Assess.* **2016**, *22*, 283–301.

49. Xue, L.Q.; Wang, J.; Zhang, L.C.; Wei, G.H.; Zhu, B.L. Spatiotemporal analysis of ecological vulnerability and management in the Tarim River Basin, China. *Sci. Total Environ.* **2019**, *649*, 876–888.

50. Wang, Y.; Ding, Q.; Zhuang, D.F. An eco-city evaluation method based on spatial analysis technology: A case study of Jiangsu Province, China. *Ecol. Indic.* **2015**, *58*, 37–46.

51. He, B.; Yun, Z.J.; Shi, J.B.; Jiang, G.B. Research progress of heavy metal pollution in China: Sources, analytical methods, status, and toxicity. *Chin. Sci. Bull.* **2013**, *58*, 134–140.

52. Ma, Z.W.; Chen, K.; Yuan, Z.W.; Bi, J.; Huang, L. Ecological Risk Assessment of Heavy Metals in Surface Sediments of Six Major Chinese Freshwater Lakes. *J. Environ. Qual.* **2013**, *42*, 341–350.

53. Teng, Y.G.; Wu, J.; Lu, S.J.; Wang, Y.Y.; Jiao, X.D.; Song, L.T. Soil and soil environmental quality monitoring in China: A review. *Environ. Int.* **2014**, *69*, 177–199.

54. Ren, H.Y.; Zhuang, D.F.; Singh, A.N.; Pan, J.J.; Qiu, D.S.; Shi, R.H. Estimation of As and Cu Contamination in Agricultural Soils Around a Mining Area by Reflectance Spectroscopy: A Case Study. *Pedosphere* **2009**, *19*, 719–726.

55. Pandit, C.M.; Filippelli, G.M.; Li, L. Estimation of heavy-metal contamination in soil using reflectance spectroscopy and partial least-squares regression. *Int. J. Remote Sens.* **2010**, *31*, 4111–4123.

56. Liu, Y.; Li, W.; Wu, G.; Xu, X.G. Feasibility of estimating heavy metal contaminations in floodplain soils using laboratory-based hyperspectral data—A case study along Le'an River, China. *Geo Spat. Inf. Sci.* **2011**, *14*, 10–16.

57. Zheng, G.H.; Zhou, S.L.; Wu, S.H. Prediction of As in Soil with Reflectance Spectroscopy. *Spectrosc. Spectr. Anal.* **2011**, *31*, 173–176.

58. Hu, Y.N.; Liu, X.P.; Bai, J.M.; Shih, K.M.; Zeng, E.Y.; Cheng, H.F. Assessing heavy metal pollution in the surface soils of a region that had undergone three decades of intense industrialization and urbanization. *Environ. Sci. Pollut. Res.* **2013**, *20*, 6150–6159.

59. Jiang, X.; Lu, W.X.; Zhao, H.Q.; Yang, Q.C.; Yang, Z.P. Potential ecological risk assessment and prediction of soil heavy-metal pollution around coal gangue dump. *Nat. Hazards Earth Syst.* **2014**, *14*, 1599–1610.

60. Dadashpoor, H.; Azizi, P.; Moghadasi, M. Land use change, urbanization, and change in landscape pattern in a metropolitan area. *Sci. Total Environ.* **2019**, *655*, 707–719.

61. Habel, J.C.; Samways, M.J.; Schmitt, T. Mitigating the precipitous decline of terrestrial European insects: Requirements for a new strategy. *Biodivers. Conserv.* **2019**, *28*, 1343–1360.

62. Folke, C.; Biggs, R.; Norstrom, A.V.; Reyers, B.; Rockstrom, J. Social-ecological resilience and biosphere-based sustainability science. *Ecol. Soc.* **2016**, *21*, 21.

63. Meerow, S.; Newell, J.P.; Stults, M. Defining urban resilience: A review. *Landsc. Urban Plan.* **2016**, *147*, 38–49.

64. Luo, W.Z.; Ren, Y.T.; Shen, L.Y.; Zhu, M.C.; Jiang, Y.M.; Meng, C.H.; Zhang, P.X. An evolution perspective on the urban land carrying capacity in the urbanization era of China. *Sci. Total Environ.* **2020**, *744*, 140827.

65. Wei, Y.G.; Huang, C.; Li, J.; Xie, L.L. An evaluation model for urban carrying capacity: A case study of China's mega-cities. *Habitat Int.* **2016**, *53*, 87–96.

66. Cohen, J.E. Population Growth and Earth's Human Carrying Capacity. *Science* **1995**, *269*, 341–346.

67. Tan, Y.T.; Xu, H.; Zhang, X.L. Sustainable urbanization in China: A comprehensive literature review. *Cities* **2016**, *55*, 82–93.

68. Xu, G.; Jiao, L.M.; Yuan, M.; Dong, T.; Zhang, B.; Du, C.M. How does urban population density decline over time? An exponential model for Chinese cities with international comparisons. *Landsc. Urban Plan.* **2019**, *183*, 59–67.

69. Lane, M. The carrying capacity imperative: Assessing regional carrying capacity methodologies for sustainable land-use planning. *Land Use Policy* **2010**, *27*, 1038–1045.

70. Fu, S.F.; Zhang, P.; Jiang, J.L. [Evaluation of land resources carrying capacity of development zone based on planning environment impact assessment]. *Ying Yong Sheng Tai Xue Bao J. Appl. Ecol.* **2012**, *23*, 459–467.

71. Liu, P.Q.; Lin, Z.S.; Feng, N.H. The Dynamic Simulation and Application of Land Population Carrying Capacity. *J. Nanjing Norm. Univ. Nat. Sci.* **2005**, *28*, 114–118.

72. Yue, W.Z.; Zhang, H.N. Research on land population supporting capacity based on ecological sensitivity-Taking Hang zhou city as an example. *Nat. Resour. Econ. China* **2013**, *26*, 52–56.

73. Salabun, W.; Watrobski, J.; Shekhovtsov, A. Are MCDA Methods Benchmarkable? A Comparative Study of TOPSIS, VIKOR, COPRAS, and PROMETHEE II Methods. *Symmetry* **2020**, *12*, 1549.

74. Malczewski, J.; Rinner, C. [Advances in Geographic Information Science]. In *Multicriteria Decision Analysis in Geographic Information Science*; Springer: Berlin/Heidelberg, Germany, 2015; doi:10.1007/978-3-540-74757-4.

75. Wang, C.; Delu, P. Zoning of Hangzhou Bay ecological red line using GIS-based multi-criteria decision analysis. *Ocean Coast Manag.* **2017**, *139*, 42–50.

76. Schaefer, M.; Nguyen Xuan, T. Evaluation of Land Cover Change and Agricultural Protection Sites: A GIS and Remote Sensing Approach for Ho Chi Minh City, Vietnam. *Heliyon* **2019**, *5*, e01773.

77. Li, J.; Xu, J.; Chu, J. The Construction of a Regional Ecological Security Pattern Based on Circuit Theory. *Sustainability* **2019**, *11*, 6343.

78. Uribe, D.; Geneletti, D.; del Castillo, R.F.; Orsi, F. Integrating Stakeholder Preferences and GIS-Based Multicriteria Analysis to Identify Forest Landscape Restoration Priorities. *Sustainability* **2014**, *6*, 935–951.

79.　Esmail, B.A.; Geneletti, D. Multi-criteria decision analysis for nature conservation: A review of 20years of applications. *Methods Ecol. Evol.* **2018**, *9*, 42–53.

80.　Rodriguez-Merino, A.; Garcia-Murillo, P.; Fernandez-Zamudio, R. Combining multicriteria decision analysis and GIS to assess vulnerability within a protected area: An objective methodology for managing complex and fragile systems. *Ecol. Indic.* **2020**, *108*, 105738.