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Assessing Suitability of Rural Settlements Using an Improved Technique for Order Preference by Similarity to Ideal Solution

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Abstract: Land suitability assessment is a prerequisite phase in land use planning; it guides toward optimal land use by providing information on the opportunities and constraints involved in the use of a given land area. A geographic information system-based procedure, known as rural settlement suitability evaluation (RSSE) using an improved technique for order preference by similarity to ideal solution (TOPSIS), was adopted to determine the most suitable area for constructing rural settlements in different geographical locations. Given the distribution and independence of rural settlements, a distinctive evaluation criteria system that differed from that of urban suitability was established by considering the level of rural infrastructure services as well as living and working conditions. The unpredictable mutual interference among evaluation factors has been found in practical works. An improved TOPSIS using Mahalanobis distance was applied to solve the unpredictable correlation among the criteria in a suitability evaluation. Uncertainty and sensitivity analyses obtained via Monte Carlo simulation were performed to examine the robustness of the model. Daye, a resource-based city with rapid economic development, unsatisfied rural development, and geological environmental problems caused by mining, was used as a case study. Results indicate the following findings: 1) The RSSE model using the improved TOPSIS can assess the suitability of rural settlements, and the suitability maps generated using the improved TOPSIS have higher information density than those generated using traditional TOPSIS. The robustness of the model is improved, and the uncertainty is reduced in the suitability results. 2) Highly suitable land is mainly distributed in the northeast of the study area, and the majority of which is cultivated land, thereby leading to tremendous pressure on the loss of cultivated land. 3) Lastly, 12.54% of the constructive expansion permitted zone and 8.36% of the constructive expansion conditionally permitted zone are situated in an unsuitable area, which indicates that the general planning of Daye lacks the necessary verification of suitability evaluation. Guidance is provided on the development strategy of rural settlement patches to support decision making in general land use planning.

Keywords: rural settlement suitability evaluation; technique for order preference by similarity to ideal solution; mahalanobis distance; Daye City

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1 Introduction

Land suitability evaluation is regarded as a process for assessing the capacity or level of a land that is suitable for a particular use by considering numerous criteria (Steiner *et al*., 2000). This process has been widely used in several fields, such as alternative agriculture (Ceballos-Silva and López-Blanco, 2003; Abdelfattah, 2013; Elsheikh *et al*., 2013), residential/commercial site selection (Bunruamkaew and Murayam, 2011; Al-Yahyai

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et al., 2012), and wildlife habitat conservation (Hazarika and Saikia, 2013; Troy *et al*., 2014). Moreover, a large number of studies have been dedicated to suitability evaluation for urban development. Dong *et al*. (2008) built an integrated urban development suitability index (SI) to analyze urban development suitability in Jingjinji, China. Dai (2001) developed a geo-environmental evaluation process for urban planning. Park *et al*., (2011) predicted and compared urban growths through land SI mapping using different approaches. Researchers have been recently looking forward to rural settlement suitability (Chen *et al*., 2013). However, such suitability remains under-investigated and lacks attention from the government in terms of planning.

Extensive development and transition in both the society and the economy of rural areas have been achieved since the implementation of economic reforms and the open-door policy in China in 1978 (Kennedy, 2010). However, the rapid urbanization and massive rural out-migration that follow the economic reforms have resulted in problems, such as urban expansion, settlement abandonment, and hollowed villages accompanied by the occupation of high-quality crop land and the wasteful use of rural settlements (Liu *et al*., 2010; Long *et al*., 2012; Tan and Li, 2013; Chen *et al*., 2014). The area of rural settlements has increased rapidly in contrast to the declining rural populations mainly at the expense of farmlands because of the lack of appropriate planning and management for existing land resources (Bai *et al*., 2014). 'Dirty, disorderly, and bad' is a widespread phenomenon in most of the current villages in China that lack scientific village planning (Long *et al*., 2009). The primary layout and design of rural settlements are currently inappropriate because of changes in cultivation methods and lifestyles (Liu *et al*., 2014; Yangang and Jisheng, 2014). In this context, the Chinese government mapped out an important long-term development strategy on 'the creation of a new socialist countryside' in 2005, which was expected to accelerate the development of agricultural and rural economies and to integrate rural with urban development (Guo *et al*., 2009). Relocating farmers to new villages or urban neighborhoods is one of the principal measures to promote the construction of a new socialist countryside (Ahlers and Schubert, 2009; 2013). This measure involves the spatial optimization of rural settlements, which focuses on countryside planning (Long *et al*., 2010). Relocating rural settlements is essential not only to accommodate to natural conditions but also to guarantee access to work and to provide education and sanitation (Bański and Wesołowska, 2010). Land suitability is assessed to adopt the best rural settlement location by identifying present and future rural geographical regions that can provide suitable living conditions. The complexity of the rural situation requires land suitability evaluation to form a new reasonable rural settlement layout through a sophisticated analysis that considers a large number of critical issues, such as topography, community, and ecology (Santé-Riveira *et al*., 2008). The assessment of the suitability of rural settlements has become a prominent challenge to countryside planning and policy development.

An appropriate selection of evaluation criteria is critical to ensure meaningful suitability evaluation results for rural settlement development. Selecting criteria that are representative, rational, and accurate to measure land suitability is crucial (Al-Shalabi *et al*., 2006). However, a standard for criteria that should be considered does not exist, and the criteria used in similar studies are generally those that are accessible, including geomorphological, socioeconomic, and environmental factors (Doygun *et al*., 2008; Cengiz and Akbulak, 2009; Akıncı *et al*., 2013; Quinn *et al*., 2014). Certain factors have been considered in special cases. For example, the risks of disasters and geological conditions have been emphasized to evaluate land suitability level for the post-earthquake reconstruction of the Lushan earthquake-stricken area (Tang *et al*., 2015). Sea level rise has been integrated into the land suitability assessment of coastal communities in New York City (Berry and BenDor, 2015). A significant unevenness exists in the allocation of service facilities because of the distribution and independence of rural settlements. In addition, rural residents experience poor living conditions in the countryside. Moreover, most members of the population continue to engage in agriculture. Thus, a significant difference exists between countryside planning and urban planning. Accordingly, appropriate factors that differ from those of urban areas should be selected. This study considered living conditions (i.e., proximity to clinics and schools) and working conditions (i.e., arable land area within farming radius) as assessment criteria that aim at land use suitability for rural residents. Constraints were considered as exclusionary criteria according to the characteristic of the study area.

Improvements are necessary in the supply and accuracy of modeling and data sets related to rural settlement suitability in local regions. An appropriate approach is required to integrate different factors and to measure both the individual and cumulative effects of these factors. A series of methods has been introduced by researchers to handle the different contributions of each criterion to the overall purpose, such as analytic network process (Pourebrahim *et al*., 2011), ordered weighted average (Yager, 1988; Romano *et al*., 2015), gravity-resistance model (Chen-jing *et al*., 2011), matter–element model (Gong *et al*., 2012), cellular automata-based spatial multi-criteria model (Yu *et al*., 2011), and technique for order preference by similarity to ideal solution (TOPSIS) (Hwang and Yoon, 1981). TOPSIS is a well-known multiple criteria decision analysis (MCDA) approach because of its good performance on MCDA problems (Kim *et al*., 1997; Shih *et al*., 2007; Behzadian *et al*., 2012). The unpredictable mutual interference among evaluation factors has been observed in practical works. The correlation among evaluation indicators in the evaluation model should be considered. An improved TOPSIS was utilized by applying the concept of Mahalanobis distance in determining the distance to ideal and negative solutions to resolve the correlation problem. Mahalanobis distance was first applied by Antucheviciene *et al*. (2010) in TOPSIS to determine the priorities of the redevelopment alternatives of buildings. Then, the properties of the improved TOPSIS were explored by Wang (2014). In recent years, some important studies on using Mahalanobis distance in TOPSIS have been conducted to assess the competitiveness of insurance corporations and select the best automobile production line (Villanueva Ponce and Garcia Alcaraz, 2013; Chen and Lu, 2014; Chen and Lu, 2015). To date, no report on the application of the improved TOPSIS on land suitability assessment is yet available. This suitability analysis provides a valuable first step in integrating geospatial technologies into the improved TOPSIS. In the present study, the improved TOPSIS was applied to address the rural settlement suitability evaluation (RSSE) problem.

Accordingly, this study aimed to propose a conceptual and methodological framework for rural settlement suitability assessment that considered the entire process—from criteria development to criteria aggregation. An evaluation criteria system that considered the level of infrastructure services, as well as living and working conditions, was developed because of the distribution and independence of rural settlements. An improved TOPSIS that used Mahalanobis distance was integrated into a geographic information system (GIS) environment to eliminate the effect of correlation in evaluation indicators. The uncertainty and sensitivity of the improved TOPSIS were analyzed using Monte Carlo simulation to validate the performance of the model. Thus, the developed suitability model is useful to governments, individuals, and researchers who are planning projects and conducting site selection in rural development.

2 Materials and Processing

2.1 Study area

The selected study area is Daye City, which is located at the southeast of Hubei Province in the central China (Fig. 1). Daye City covers an area of approximately 1556.97 km^2 (29°51′–30°20′N, 114°31′–115°11′E). It has a population of 962 300 in 2013, among which 422 200 comprise the rural population. The area of rural settlement is 118.50 km^2, and the per capita rural settlement area reaches up to 280 m^2, which is significantly higher than the national land use standard.

Daye is a resource-based city with rich mineral resources. As one of the top 100 counties in China, Daye enjoys sound economic development that relies on mineral resources. However, natural resource depletion has exhausted its mineral resources; simultaneously, numerous problems, such as a single and unbalanced economic structure, lack of growth potential, and serious ecological damage, have severely affected the sustainable development of Daye. According to the Industrial and Mining Wasteland Reclamation Planning of Daye, 71.69 km^2 of the industrial and mining wasteland of the city has induced geological environmental problems that affect residential building security. The influence of industrial and mining wasteland caused by resource overexploitation during the suitability evaluation of rural settlements should be considered. In Daye, the sluggish growth of the rural economy and the slow increase in the income of farmers has lowered the living standards of farmers. In 2013, the average urban disposable income of Daye was 23 063 yuan (RMB),

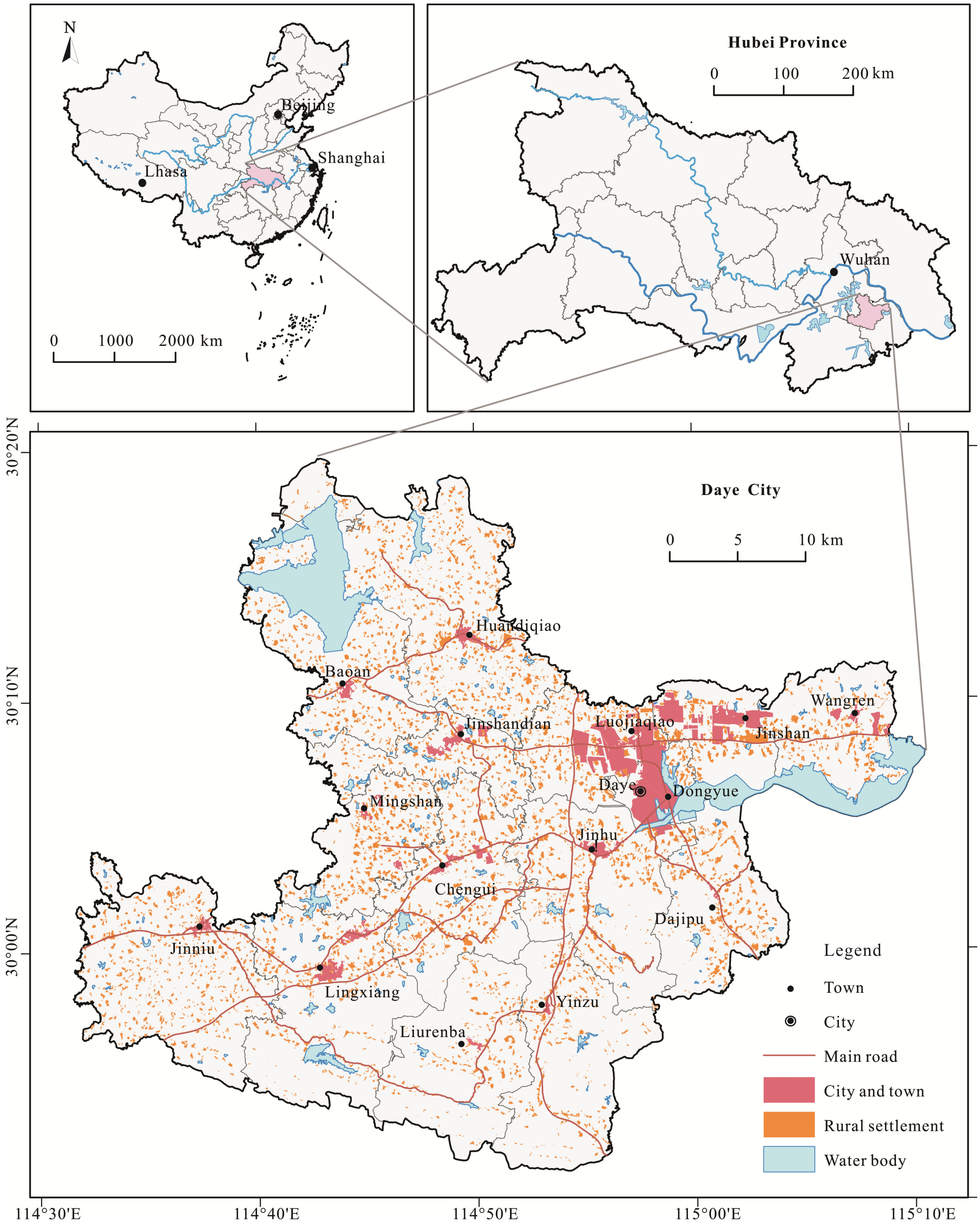

Fig. 1 Location of study area and overview of its rural settlements

whereas the rural per capita net income was 10 616 yuan (RMB). The income gap between the rural and urban populations has widened from 1.92 to 1.00 in 1978 to 2.17 to 1.00 in 2013. The creation of a new socialist countryside has been widely implemented in Daye to reduce income gap and promote rural development. The rural planning survey of 110 unincorporated villages has been completed in the last few years, and countryside planning is required at the present stage. Thus, the RSSE model can contribute to countryside planning.

2.2 Data sources and processing

The data used in this study were collected from various sources (Table 1). Land use data, including the road map of the study area, were derived from the 1 : 10 000 land use map based on land utilization alteration data in 2012. The digital elevation model (DEM), with a spatial resolution of 30 m × 30 m, was obtained from the International Scientific Data Service Platform. Slope and aspect were generated with the DEM using 3D analyst tools in ArcGIS 10.0. The hazardous areas resulting from mining were extracted from the status quo map of the industrial and mining wasteland distribution. The distribution of public service facilities was obtained through specific investigation and mapping via a field survey. A normalized difference vegetation index (NDVI) map to represent the vegetation cover for the study area was generated using a digitally processed Landsat 7 TM image taken in 2010. The constructive expansion permitted zone and the constructive expansion conditionally permitted zone were extracted from the zoning map for regulating the constructive expansion. The population status of each rural settlement patch was gathered by conducting a questionnaire survey with the village head.

Prior to further processing, all data were converted or resampled into raster data with a resolution of 30 m × 30 m through ArcGIS 10.0. The RSSE model based on the improved TOPSIS and Monte Carlo simulation was developed using MATLAB 8.0, and the spatial explicit results were mapped using ArcGIS 10.0.

3 Methods

Three major phases of the methodology were adopted in the RSSE model using an improved TOPSIS, namely, criteria development, suitability classification and weight assigning, and criteria aggregation. Figure 2 shows the three phases of the model. The details of the major processes are presented in the following subsections.

3.1 Criteria development

The suitability of rural settlements is influenced by several factors. The design of evaluation criteria depends on resource endowment, major demand, and the contradiction of local residents. In addition, criteria should be subjected to certain principles, including maturity, objectivity, consistency, measurability, accessibility, dynamics, and relative stability (Zhang and Chen, 2011).

Evaluation criteria were classified into two principal categories, namely, exclusionary criteria (constraints) and opportunity criteria, which involved topography, community characteristics, and ecological factors. Exclusionary criteria refer to factors that limit construction to certain geographic areas (Jeong *et al.*, 2014). Opportunity criteria are adopted to reflect the degree of opportunity (or suitability) using quantitative or ranked values allocated to all mapping units (Liu *et al.*, 2014). In particular, 7 exclusionary criteria and 17 opportunity criteria were introduced into the suitability evaluation process (Dong *et al.*, 2008; Emami and Zarkesh, 2011; Liu *et al.*, 2014). Exclusionary criteria include the following: 1) surface water bodies; 2) collapse area; 3) mined-out region; 4) landslide region; 5) cover occupation area; 6) excavation area; and 7) pollution area. Opportunity criteria include the following: 1) elevation; 2) slope; 3) aspect; 4) proximity to cities; 5) proximity to towns; 6) proximity to village committees; 7) proximity to roads; 8) proximity to hospitals; 9) proximity to clinics; 10) proximity to high schools; 11) proximity to middle schools; 12) proximity to primary schools; 13) proximity to kindergartens; 14) arable land area within farming radius; 15) land use and cover type; 16) proximity to water bodies; and 17) vegetation. The details of each subcriterion are shown in Tables 2 and 3. The criteria setup was selected according to local characteristics, authenticated literature, and the opinions of experts.

Table 1 List of data and their original sources

Data	Scale	Source
Land use map 2012	1 : 10 000	Daye Bureau of Land and Resources
DEM	30 m × 30 m	International Scientific Data Service Platform
Status quo map of 'industrial and mining wasteland distribution'	1 : 10 000	Daye Bureau of Land and Resources (Industrial and Mining Wasteland Reclamation Planning of Daye)
Map of zoning for 'regulating the constructive expansion'	1 : 10 000	Daye Bureau of Land and Resources (General Land Use Planning of Daye)
Distribution of public service facilities		Field survey with GPS
Landsat 7 TM image (2010)	30 m × 30 m	International Scientific Data Service Platform
Population status of each rural settlement patch		Questionnaire survey against the village head

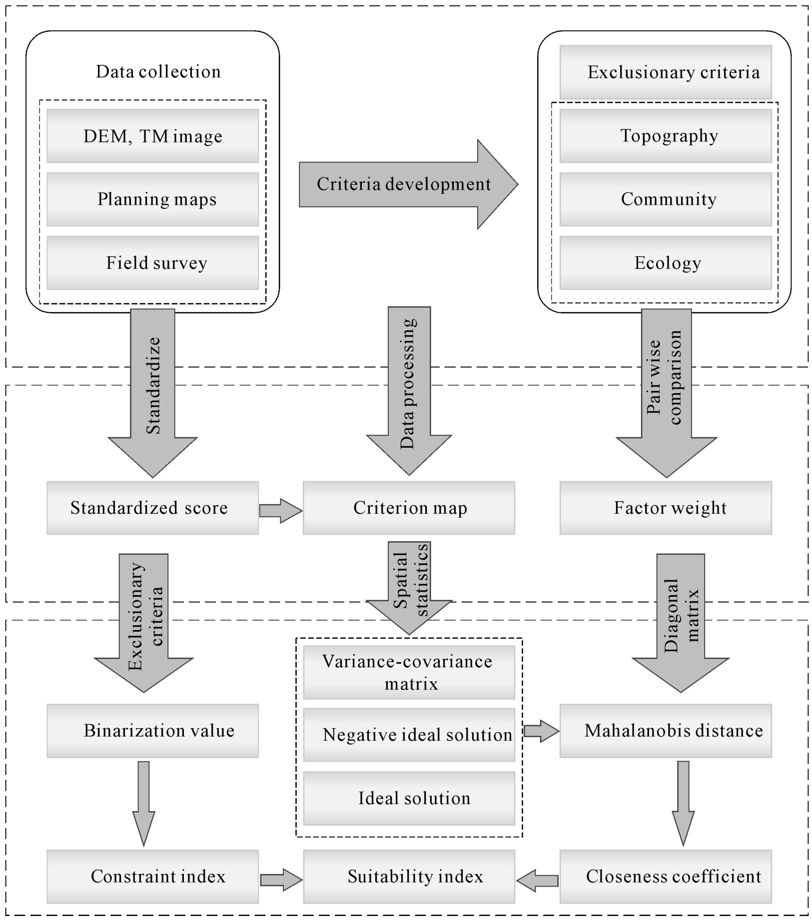

Fig. 2 Procedure of RSSE model using improved TOPSIS

Table 2 Subcriteria of exclusionary criteria

Sub-criteria	Description
Surface water bodies (SWB)	Areas whose status quo is the land of waters, including lakes, reservoirs and rivers
Collapse area (CA)	Areas that have collapsed caused by underground mining
Mined-out region (MOR)	Areas excavated and hollowed out by underground mining
Land slide region (LSR)	Areas damaged of threatened by land slide hazard
Cover occupation area (COA)	Areas used to pile up mineral waste and difficult to control its potential pollution threat
Excavation area (EA)	Areas with open pit surrounded by excavation mines
Pollution area (PA)	Areas polluted by tailings ponds or storing slag and waste residue

3.2 Suitability classification and weight assigning of criteria

Based on the previously defined criterion index, values were derived and standardized for the opportunity and exclusionary factors before these non-commensurate criteria were combined. Exclusionary criteria were quantized into binary form ′0–1′ (0 for the area with exclusionary criteria constraints, and 1 for the area without exclusionary criteria constraints) (Jeong *et al.*, 2014). A scoring and ranking system was used to quantify the suitability levels of the opportunity factors from 1 to 4 (Table 4), according to literature review and expert opinions (Pourebrahim *et al.*, 2011; Gong *et al.*, 2012). A high score denotes that the area has high suitability.

These opportunity criteria were assigned with different weights based on their various influences on rural settlement suitability. The pairwise comparison method was used to calculate the weights of each criterion. The 9-point weighing scale of Saaty (1977) was applied to

Table 3 Subcriteria of opportunity criteria

Criteria	Sub-criteria	Description
Topography	Elevation (ELE)	Areas showing the basic parameter of altitude
	Slope (SLO)	Areas showing topographic relief expressed in degrees
	Aspect (ASP)	Areas showing the basic orientation of the terrain
Community	Proximity to cities (PTC)	Areas calculated using Euclidean distance functions, the radial distance from cities representing a convenient access to the cities
	Proximity to towns (PTT)	Areas calculated using Euclidean distance functions, the radial distance from towns representing a convenient access to the towns
	Proximity to village committees (PTVC)	Areas calculated using Euclidean distance functions, the radial distance from village committees representing a convenient access to the political center at a local level
	Proximity to roads (PTR)	Areas calculated using Euclidean distance functions, the radial distance from roads representing a better transportation condition
	Proximity to hospitals (PTH)	Areas calculated using Euclidean distance functions, the radial distance from hospitals representing a better medical service
	Proximity to clinics (PTCL)	Areas calculated using Euclidean distance functions, the radial distance from clinics representing a better medical service
	Proximity to high schools (PTHS)	Areas calculated using Euclidean distance functions, the radial distance from high schools representing a better senior secondary educational level
	Proximity to middle schools (PTMS)	Areas calculated using Euclidean distance functions, the radial distance from middle schools representing a better compulsory educational level
	Proximity to primary schools (PTPS)	Areas calculated using Euclidean distance functions, the radial distance from primary school representing a better elementary educational level
	Proximity to kindergartens (PTK)	Areas calculated using Euclidean distance functions, the radial distance from kindergartens representing a better pre-school educational level
	Arable land area in farming radius (ALA)*	Areas calculated the area around the farming radius representing the cultivation basic conditions
Ecology	Land use and cover type (LUCT)	Areas covering different land use and cover types playing different roles in the ecological system
	Proximity to water bodies (PTWB)	Areas calculated using Euclidean distance functions, the radial distance from water bodies representing the influence to the aquatic ecosystems
	Vegetation (VEG)	Areas with different levels of vegetation formation using the normalized difference vegetation index (NDVI)

Note: * Farming radius is defined as 2.5 km by distance walking for 30 min at 5 km/h

develop a pairwise comparison matrix. This scale ranges from 1 to 9, with 1 indicating equal importance between two criteria, 9 indicating extreme importance, and the numbers in between indicating different degrees of importance. The relative importance of the factors was identified by asking for advice from local residents and experts, and 12 usable responses were obtained out of 13. The weight values could be derived by taking the principal eigenvector of the square reciprocal matrix of the pairwise comparison and then normalizing the sum of the components to a unity (Saaty, 1977). The consistency of the comparison matrices was tested and proven acceptable. The weight of each evaluation factor was determined. The results are presented in Table 4.

3.3 Procedure for aggregating criteria

RSSE is a spatial MCDA procedure. We adopted each geographical evaluation unit as an independent alternative and each geographical indicator represented as map layers were regarded as evaluation criterion (Malczewski, 2006). Topography, community, and ecological factors were considered in the evaluation method. SI was received as the final output of the evaluation through the trade-off among the three types of factors. The overall procedure of the RSSE model using the improved TOPSIS operator structure is shown in Fig. 2.

First, exclusionary criteria were used to exclude areas that were obviously unsuitable for rural settlements. The constraint index is calculated as follows:

Table 4 Ranking, scoring, and weights of opportunity factors for rural settlement suitability evaluation (RSSE)

Rank	Highly suitable	Moderately suitable	Marginally suitable	Unsuitable	Weights
Score	4	3	2	1	
ELE (m)	≤30	30–200	200–500	>500	0.0519
SLO (°)	≤5	5–15	15–25	>25	0.1101
ASP	Flat	South	East or west	North	0.0121
PTC (m)	≤10 000	10 000–20 000	20 000–30 000	>30 000	0.1502
PTT (m)	≤2000	2000–4000	4000–6000	>6000	0.1106
PTVC (m)	≤1000	1000–2000	2000–3000	>3000	0.0207
PTR (m)	≤1000	1000–2000	2000–3000	>3000	0.1222
PTH (m)	≤2000	2000–4000	4000–6000	>6000	0.0312
PTCL (m)	≤1000	1000–2000	2000–3000	>3000	0.0553
PTHS (m)	≤2000	2000–4000	4000–6000	>6000	0.0344
PTMS (m)	≤1000	1000–2000	2000–3000	>3000	0.0634
PTPS (m)	≤1000	1000–2000	2000–3000	>3000	0.0639
PTK (m)	≤2000	2000–4000	4000–6000	>6000	0.0432
ALA (hm^2)	>1000	600–1000	300–600	≤300	0.0275
LUCT	build-up, wasteland	Grasslands, sparse woodland	other agricultural land, orchard, closed forest land	cultivated land, water body	0.0608
PTWB (m)	>200	140–200	100–140	≤100	0.0260
VEG	≤0.1	0.1–0.2	0.2–0.3	>0.3	0.0165

Notes: ELE, elevation; SLO, slope; ASP, aspect; PTC, proximity to cities; PTT, proximity to towns; PTVC, proximity to village committees; PTR, proximity to roads; PTH, proximity to hospitals; PTCL, proximity to clinics; PTHS, proximity to high school; PTMS, proximity to middle schools; PTPS, proximity to primary schools; PTK, proximity to kindergartens; ALA, arable land area in farming radius; LUCT, land use and cover type; PTWB, proximity to water bodies; VEG, vegetation

$$CI = \prod_{k=1}^{l} e_k \tag{1}$$

where CI is the constraint index; e_k is the criterion score of exclusionary criterion k; and l is the number of exclusionary criteria.

Second, the suitability values of opportunity criteria were calculated using the improved TOPSIS. In TOPSIS, the best alternative should be selected to exhibit the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution simultaneously (Chen and Tzeng, 2004; Sakthivel *et al*., 2015). The positive ideal solution maximizes the benefit criteria/attributes and minimizes the cost criteria/attributes, whereas the negative ideal solution maximizes the cost criteria/attributes and minimizes the benefit criteria/attributes (Wang and Elhag, 2006; Aloini *et al*., 2014).

Situations in geography and humanities vary geographically (Démurger, 2001; Cai *et al*., 2002). An unpredictable correlation may exist among indices. Mahalanobis distance was integrated into traditional TOPSIS to promote a widely applicable method that could eliminate the correlation problem when rural settlement suitability was evaluated. Mahalanobis distance is a statistical distance proposed by Mahalanobis (1936). It considers the correlation of criteria vectors because it is calculated using the inverse of the variance-covariance matrix of the multiple criteria matrix (Xiang *et al*., 2008).

The i sample point is represented by $x_i = (x_{i1}, x_{i2}, \ldots, x_{im})^T$. The Mahalanobis distance between two points, x_1 and x_2, can be calculated as follows:

$$d(x_1, x_2) = \sqrt{(x_1 - x_2)^T C^{-1} (x_1 - x_2)} \tag{2}$$

where C is the variance-covariance matrix constructed from the data set X; thus, C is positively semi-definite. The improved TOPSIS can be summarized as follows.

An MCDA problem is supposed to have n alternatives $S_1, S_2, \ldots, S_n$. Each alternative has m decision criteria, $C_1, C_2, \ldots, C_m$. All the alternatives were evaluated with respect to m criteria, and a decision matrix denoted by $X = (x_{ij})_{n\times m}$ was formed. The decision matrix was normalized in advance to eliminate dimensional influence.

The Mahalanobis distances of each alternative x_i to the ideal solution (S^+) and the negative ideal solution (S^-) can be calculated, respectively, as follows:

$$d\left(x_i, S^+\right) = \sqrt{\left(S^+ - x_i\right)^T \Omega^T C^{-1} \Omega \left(S^+ - x_i\right)}$$

$$i = 1, 2, \ldots, n \qquad (3)$$

$$d\left(x_i, S^-\right) = \sqrt{\left(x_i - S^-\right)^T \Omega^T C^{-1} \Omega \left(x_i - S^-\right)}$$

$$i = 1, 2, \ldots, n \qquad (4)$$

With regard to decision matrix X that contains n alternatives and is measured for m criteria, the variance–covariance matrix C was initially constructed. We used the diagonal matrix of the weight vector Ω, where ω is the relative weights of the criteria and m is the number of opportunity criteria, as follows:

$$\Omega = diag\left(\sqrt{\omega_1}, \sqrt{\omega_2}, \ldots, \sqrt{\omega_m}\right) \qquad (5)$$

By calculating the closeness coefficient of each alternative to the ideal solution, the relative closeness of alternative S_i is defined as follows:

$$CC_i = \frac{d\left(x_i, S^-\right)}{d\left(x_i, S^-\right) + d\left(x_i, S^+\right)} \qquad (6)$$

The preference of the i-th alternative is indicated by CC_i. A high CC_i value indicates that S_i is an appropriate alternative, and vice versa.

Finally, the mathematical equation used to assign the overall SI, which applies both exclusionary and non-exclusionary criteria, is as follows:

$$SI_i = CI_i \times CC_i \qquad (7)$$

where SI_i is the overall suitability index of the i-th alternative (geographical evaluation unit), CI_i is the constraint index calculated using exclusionary criteria, and CC_i is the closeness coefficient calculated using non-exclusionary criteria.

3.4 Uncertainty and sensitivity analyses

Uncertainty and sensitivity analyses are required to examine the robustness of the evaluation model and confirm the stability of the results (Delgado and Sendra, 2004). Criterion weight is one of the most important uncertainty sources derived from expert judgments (Benke and Pelizaro, 2010). Criterion weight uncertainty and sensitivity in the RSSE model were analyzed using Monte Carlo simulation. Weight samples expressed in probability distributions were applied to the RSSE model to realize Monte Carlo simulation, and the final output probability distribution for each iteration of the model was generated (Ligmann-Zielinska and Jankowski, 2014). The uncertainty and sensitivity metrics of the RSSE model could then be derived from this distribution.

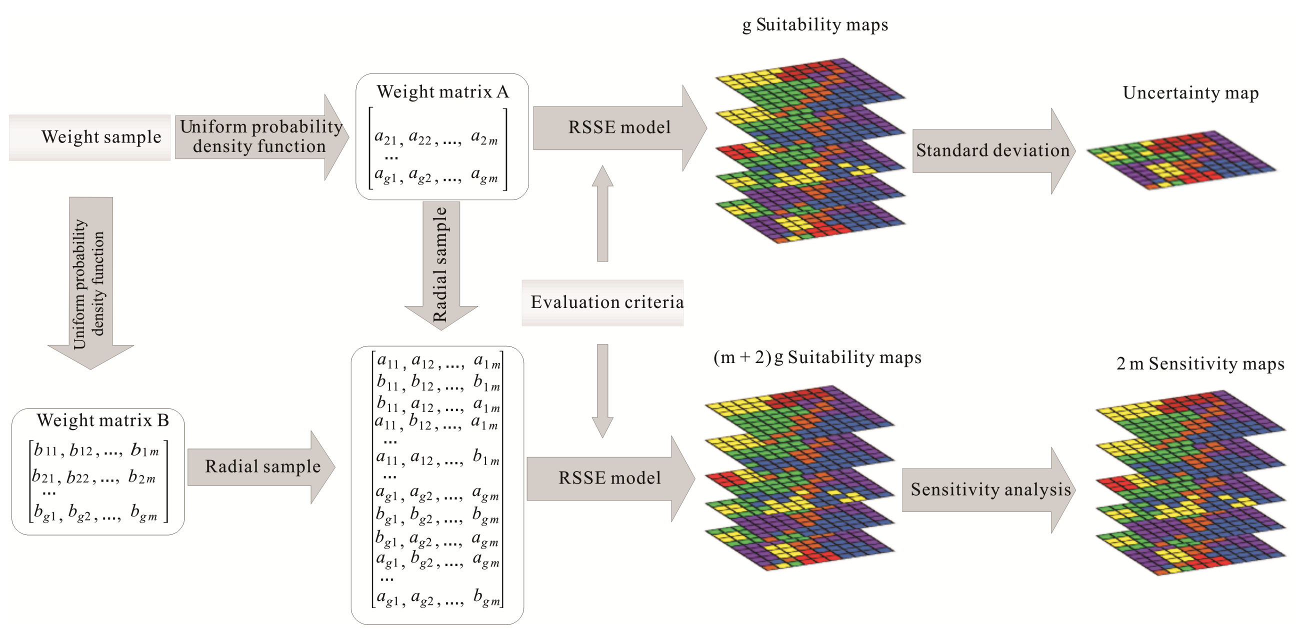

Fig. 3 Procedures for uncertainty and sensitivity analyses of suitability weights

Uncertainty analysis was performed using MATLAB 8.0. The work flow is shown in Fig. 3. First, two independent lists of g weight samples were generated based on uniform probability density function with a range of [0.0, 1.0] to represent the uncertainty of m criteria weights, which were referred to as sample lists A and B. Second, a series of output suitability maps was calculated with the RSSE model using all the weight vectors in A, given that either of the two sample lists was independent and sufficient to compute an entire range of model responses. Finally, standard deviation (STD) surfaces were calculated to represent the uncertainty surface.

The sensitivity of the model was measured using the first-order effect index (referred to as *SF* hereafter) and the total effect index (referred to as *ST* hereafter) of each factor. SF_i measures the first-order (e.g., additive) effect of the given criterion weight of the i-th generic factor C_i on the variance of the model output. A larger value of this effect denotes a larger influence on suitability score variability. ST_i measures the overall effect of a given weight of the i-th generic factor C_i, including its interactions with other weights (and, indirectly, other suitability criteria). Both sets of indices, SF_i and ST_i, were estimated by following the radial sample procedure proposed by Saltelli *et al*. (2010). The procedure begins from the two weight samples, A and B, which has been generated earlier. We adopted a_{ji} and b_{ji} as the generic elements of A and B. In these elements, index i runs from one to m, that is, the number of factors, whereas index j runs from one to g, that is, the number of simulations. We subsequently introduced radial weight sample $A_B^{(i)}$ ($B_A^{(i)}$), wherein all columns were from A (B) except for the i-th column, which was substituted with value b from an equivalent sample in B (A). For example, for the weight sample [a_{j1}, a_{j2}, a_{j3}, … a_{ji}, … a_{jm}], m radial samples $A_B^{(i)}$ are generated in the following form:

$$[a_{j1},\ a_{j2},\ a_{j3},\ \dots\ b_{ji},\ \dots\ a_{jm}] \tag{8}$$

We obtained $(m + 2)g$ weight samples. For a convenient discussion, the function of the RSSE model with regard to weight was given in the form of $Y = f(w_1, w_2, w_3, \dots w_m)$, with Y as the suitability map generated using the RSSE model.

SF_i can be computed as follows:

$$SF_i = \frac{1}{g}\sum_{j=1}^{g} f(A)_j \left(f\left(B_A^{(i)}\right)_j - f(B)_j \right) \tag{9}$$

ST_i can be computed as follows:

$$ST_i = V(Y) - \frac{1}{g}\sum_{j=1}^{g} f(A)_j \left(f(A)_j - f\left(A_B^{(i)}\right)_j \right) \tag{10}$$

where $V(Y)$ is the variance of the model output Y obtained throughout the radial samples.

4 Results and Discussion

4.1 Comparison between traditional TOPSIS and improved TOPSIS

Two suitability location maps were generated using traditional TOPSIS and the improved TOPSIS, as shown in Fig. 4, to verify the use of the improved TOPSIS.

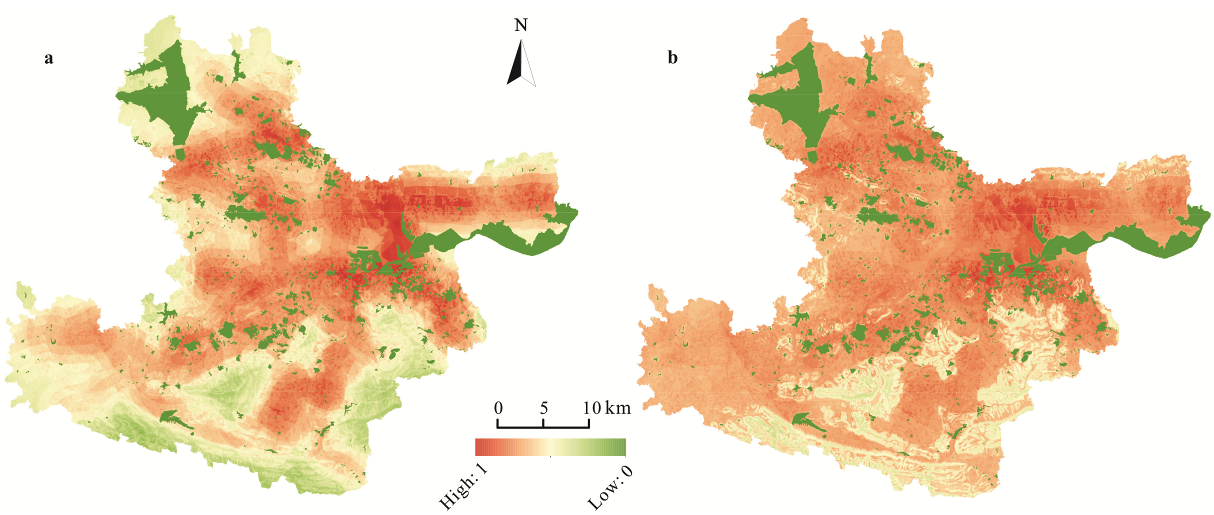

Fig. 4 Suitability surface using traditional TOPSIS (a) and improved TOPSIS (b)

The suitability evaluation map produced using traditional TOPSIS shows an obvious pattern of 'pole–axle–circle' because of an intense preference for proximity to towns and proximity to roads. Both factors exhibit a strong correlation and reinforce each other's influence on the suitability evaluation results. The suitability evaluation results are dominated by the distribution of roads and towns. However, residents no longer care for proximity to roads when proximity to towns is satisfied, and other factors become more important. For example, high schools and kindergartens are distributed mainly in the urban district of the city. The influence of proximity to cities includes the influence of high schools and kindergartens to a certain extent. The improved TOPSIS reduces the influence of correlation among factors, and a reasonable suitability evaluation map is obtained. The suitability evaluation map based on the improved TOPSIS provides more details of the evaluation variance than the map based on traditional TOPSIS, and differences in other evaluation factors are also reflected. The suitability evaluation map produced using the improved TOPSIS reduces the preference of the interaction factors and increases emphasis on independent factors.

Two frequency histograms are shown in Fig. 5 to compare the statistical distributions of the evaluation results. For a convenient comparative analysis, the raster cells in the constrained area with 0 SI are not involved in the statistical distributions.

The suitability evaluation map obtained using traditional TOPSIS exhibits equilibrium distribution around varied suitability values. By contrast, the suitability value obtained using the improved TOPSIS is more concentrated within the scope of 0.5–0.7. This result is in accordance with the practical situation because only a small area is extremely suitable or unsuitable for rural settlements. All the factors in the highly suitable area will be in good condition. An area that is in poor condition will be marked as unsuitable.

4.2 Uncertainty and sensitivity analyses

The uncertainty and sensitivity analyses of the two suitability evaluation methods were performed following the method proposed in Section 2.3. According to this method, two independent lists of 2240 weight samples of the 17 criteria weights were generated, which were referred to as sample lists W_A and W_B. The weight samples of each criterion were defined in accordance with the uniform distribution within the range of 0 to 1. The simulated maps for rural settlement suitability in the study area were generated using one of the sample lists, that is, W_A. Uncertainty analysis was conducted using the listed 2240 simulated maps. The spatial distribution of the uncertainty index represented by the STD values of the simulated maps was generated, as shown in Fig. 6 (Yeh and Tung, 1993).

The mean STD value of the simulated maps obtained using traditional TOPSIS is 0.064, whereas that of the simulated maps obtained using the improved TOPSIS is 0.041. The improved TOPSIS increased robustness and obviously reduced uncertainty. Additional details of the uncertainty change can be determined by comparing the spatial distribution map of the STD value based on traditional TOPSIS with that based on the improved TOPSIS. The high uncertainty value area is distributed in the northwest and eastern parts of the study area in the map generated using traditional TOPSIS. By contrast, the high uncertainty value area is distributed in the southwest and northeast parts of the study area and is

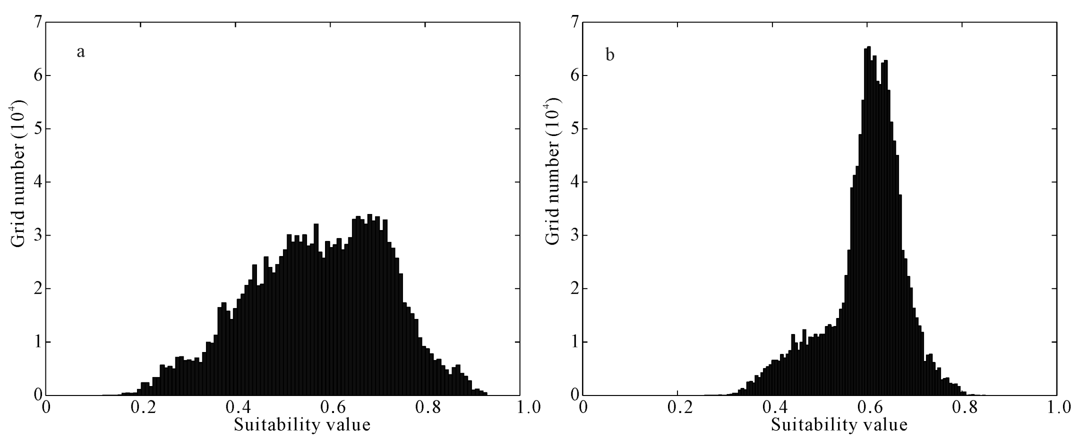

Fig. 5 Histogram of suitability surface using traditional TOPSIS (a) and improved TOPSIS (b)

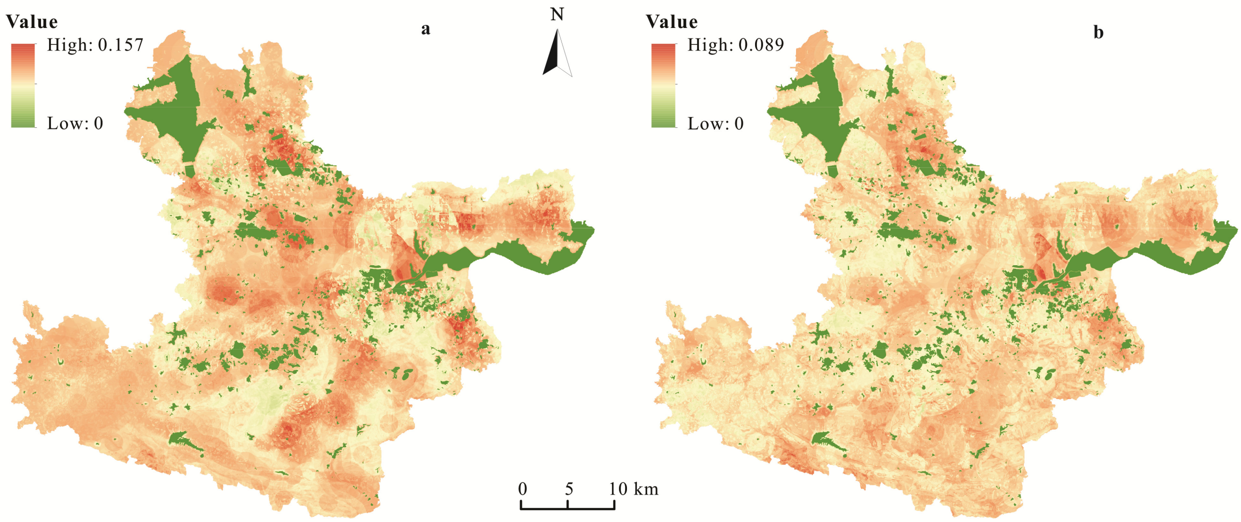

Fig. 6 Uncertainty (STD value) distribution map of RSSE obtained using traditional TOPSIS (a) and improved TOPSIS (b)

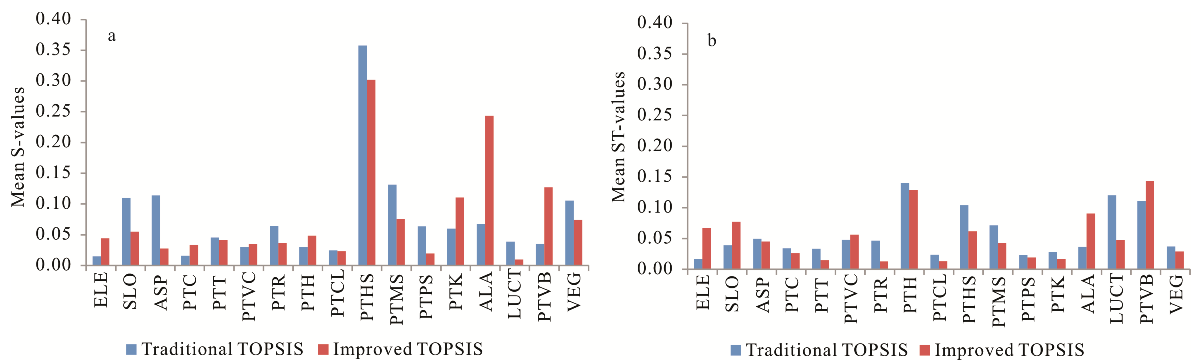

Fig. 7 Mean first-order sensitivity values (a) and total effect sensitivity values for each RSSE criterion (b). ELE, Elevation; SLO, Slope; ASP, Aspect; PTC, Proximity to cities; PTT, Proximity to towns; PTVC, Proximity to village committees; PTR, Proximity to roads; PTH, Proximity to hospitals; PTCL, Proximity to clinics; PTHS, Proximity to high school; PTMS, Proximity to middle schools; PTPS, Proximity to primary schools; PTK, Proximity to kindergartens; ALA, Arable land area in farming radius; LUCT, Land use and cover type; PTWB, Proximity to water bodies; VEG, Vegetation

concentrated in a small area in the map generated using the improved TOPSIS. Sensitivity analysis was conducted based on the method proposed in Section 2.3 to investigate the primary factors that contributed to the fluctuation of the suitability value.

Sensitivity analysis was performed on the RSSE criteria to determine the sensitivity of the SI to changes in criteria weights. Based on the method in Section 2.3, the S value maps and ST value maps of each evaluating factor were generated in the study area. The mean S-values and ST-values of each factor were calculated in the map, as shown in Fig. 7. A significant difference exists in the sensitivity index affected by the changes in the weighting of various evaluating factors. The mean S-values and ST-values of each factor obtained using traditional TOPSIS and the improved TOPSIS, respectively, are different to a certain extent. The mean S-values of elevation, proximity to kindergartens, arable land area within farming radius, and proximity to water body obtained using the improved TOPSIS are significantly larger than those obtained using traditional TOPSIS. The mean S-values of slope, aspect, proximity to high schools, and proximity to middle schools obtained using the improved TOPSIS are significantly smaller than those obtained using traditional TOPSIS. The mean ST-values of each factor are generally smaller than their S-values. The disparity between the ST-values obtained using the improved TOPSIS and traditional

TOPSIS is relatively smaller than that for the S-values because the ST-value measures the overall effect of a given factor, including its interactions with other factors. Consequently, its effect is consistent with that of the improved TOPSIS.

4.3 Distribution of suitable areas

The RSSE value was classified into four categories based on the natural breaking point method in ArcGIS 10.0, as shown in Table 5 and Fig. 8. The four categories, from high to low, are highly suitable, moderately suitable, marginally suitable, and unsuitable. The highly suitable area is primarily distributed in the northeast of the study area. The total area under the highly suitable class is roughly 523.80 km^2 (33.63% of Daye). Such land mostly has convenient traffic and good infrastructure conditions. The moderately suitable area is principally distributed in the west and north parts of the study area and is approximately 654.89 km^2 (42.07%). The traffic conditions in such land are not too good. Moreover, the flat topography of this area is barely satisfactory for rural inhabitants. The marginally suitable area is primarily distributed in the southeast part of the study area. The rugged terrain reduces the degree of development in this area, and living in this area is inconvenient. A total area of roughly 212.08 km^2 (13.63%) is categorized as marginally suitable for rural settlement. The unsuitable areas, with approximately 166.20 km^2 (10.67%), are distributed sporadically in the center, northeast, and northwest parts of the study area. Such areas are mainly lakes, reservoirs, and industrial and mining lands.

As shown in Table 5, a significant difference exists in the areas of various land uses in each suitability class. Most built-up land belongs to the high suitability class because of continuous development and utilization. However, 33.01 km^2 of built-up land is under the unsuitability class. These built-up areas should be either reinforced or relocated. Cultivated land mainly belongs to the high suitability and moderate suitability classes. Such land also comprises the largest portion in the high suitability class because it always has good location and water resources. The result signifies that the protection of cultivated land is under considerable pressure. The areas of forests, grasslands, and water bodies in the high suitability class are small because of environmental protection.

4.4 Implications

An improved TOPSIS was applied in this study to determine the optimal land suitability for rural settlements, which could be used to support decisions on land use planning. The method can help planners enhance their understanding of local conditions, and thus, facilitate their accurate, judicious, and timely decision making (Pourebrahim and Hadipour, 2011). On the one hand, this model can help select the best alternatives to future rural settlements. On the other hand, this model can help identify inhospitable areas where rural settlements should be consolidated or relocated. The general land

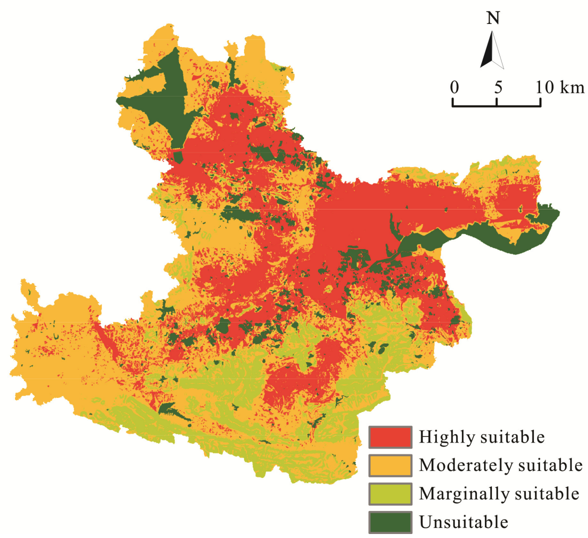

Fig. 8 Suitability category map of study area

Table 5 Area of different land uses in each suitability class (km^2)

Suitability class	Land use categories						Total
	Built-up	Cultivated land	Forest	Grassland	Water body	Unutilized land	
Highly suitable	162.99	230.56	73.82	18.20	32.85	5.38	523.80
Moderately suitable	37.67	322.00	203.48	17.51	62.84	11.39	654.89
Marginally suitable	2.21	11.86	188.43	4.21	0.84	4.53	212.08
Unsuitable	33.01	24.59	9.09	2.31	96.26	0.94	166.20
Total	235.88	589.01	474.82	42.23	192.80	22.23	1556.97

Table 6 Suitability classes of regions in constructive expansion permitted zone and constructive expansion conditionally permitted zone

Suitability class	Constructive expansion permitted zone		Constructive expansion conditionally-permitted zone	
	Area (km^2)	Percentage (%)	Area (km^2)	Percentage (%)
Highly suitable	185.85	70.23	58.21	70.51
Moderately suitable	43.88	16.58	16.98	20.57
Marginally suitable	1.72	0.65	0.47	0.56
Unsuitable	33.19	12.54	6.90	8.36

use planning of Daye (2010–2020) was implemented in 2012. One of the most important elements of the aforementioned planning is the demarcation of the constructive expansion permitted zone and the constructive expansion conditionally permitted zone. The former is the region where urban and rural constructions are permitted in the planning period. By contrast, the latter is the region where urban and rural constructions are permitted only when certain conditions are satisfied in the planning period. We overlaid the microzonation map and the suitability category map. The results indicate that the two demarcated zones are primarily located in highly suitable areas, with proportions of up to 70.23% and 70.51%, respectively. However, as shown in Table 6, 12.54% of the constructive expansion permitted zone and 8.36% of the constructive expansion conditionally permitted zone are situated in unsuitable areas. In this context, these areas do not satisfy construction demand, and building rural settlements in such areas should be avoided. This observation indicates that the compilation of the general land use planning of Daye lacks investigation and evaluation.

This study analyzed the development strategy of rural settlement patches in Daye in terms of the suitability class and population size of rural settlement patches to provide specific guidance for rural settlement land consolidation and new construction. The rural settlement patches were divided into four development types, namely, urbanization-oriented, priority, restricted expansion, and relocation, according to the following rules. Rural settlement patches located in unsuitable class were defined as relocation development type because of the insecurity condition or harmful environmental influence. Small rural settlement patches (Living population < 200 m^2, GB 50188-2007. Ministry of Construction of the People′s Republic of China, 2007. Standard for planning of town: China building industry press) located in the area marked as marginally suitable class were also defined as relocation development type. Rural settlement patches adjacent to cities and towns were defined as urbanization-oriented development type, given the advantages in developing second and third industries. Large rural settlement patches (Living population ≥ 600 m^2 GB 50188-2007. Ministry of Construction of the People′s Republic of China, 2007. Standard for planning of town: China building industry press) located in highly suitable class were defined as priority development type because of the good living and production conditions. The remaining rural settlements were defined as restricted expansion development type.

The spatial distributions of the rural settlement patches in each development type are shown in Fig. 9. Among the 4727 patches, 612 were categorized under urbanization-oriented development type, and the population was 74 250. These rural settlement patches were undoubtedly distributed around cities and towns, with an area of 2057.60 ha (Table 7). The residents of these rural settlements were encouraged to engage in secondary and tertiary industries and to change their rural lifestyle to an urban lifestyle. Among the 4727 patches, 103 were categorized under priority development type, and the population was 55 850. These rural settlement patches were mainly distributed northeast of Daye, with an area of 1407.79 hm^2, because the downtown section of the study area was located near these patches. In these areas, measures should be taken to increase the integrity of infrastructure and to provide infrastructure services for the surrounding area. A total of 7848 patches with a population of 272 810 were classified under the restricted expansion development type. These rural settlements with poor infrastructure condition were experiencing population emigration. These areas were also guided on the intensive use of land to prevent disorganized expansion. A total of 264 patches were defined as relocation development type with an area of 537.09 ha. A total of 19 290 population should migrate to neighborring villages or be resettled by the government. The evaluation of rural settlement suitability resulted in the suggestion of future rural settlement development.

In addition to the agricultural function of rural areas, socioeconomic factors play important roles (Chisholm, 1972). This research presented a distinctive criterion that considered both natural and socioeconomic factors. Moreover, geological and environmental problems induced by resource mining were regarded as critical factors in rural settlements as a result of the damage to such settlements caused by resource mining. Similar problems occur in other resource-based cities, wherein disaster levels continue to increase and losses are severe (Li *et al*., 2013). A total of 69 cities in China are designated as resource-exhausted cities and are confronted with the same problems as Daye (Li *et al*., 2013). The presented criterion can be used to evaluate the suitability of rural settlements in other resource-based cities. However, it should be improved and supplemented according to local conditions to spread the utilization of the RSSE model further. This research used a uniform evaluation model to assess the overall extent of a rural area. Nevertheless, an obvious differentiation of land-use structure exists between a near-urban countryside and a rural hinterland (Zhu *et al*., 2014). To enhance the evaluation result, the differentiation of land use and function of rural settlements should be considered.

5 Conclusions

This study proposed a scientifically founded approach known as RSSE based on improved TOPSIS to assess the suitability of rural settlement development. A comprehensive evaluation criteria system, which was divided into exclusionary criteria and opportunity criteria, was established according to rural settlement characteristics. Mahalanobis distance was used to solve the correlation problem among evaluation factors in improved TOPSIS. The uncertainty and sensitivity of the rural settlement suitability maps produced using the improved TOPSIS were analyzed via Monte Carlo simulation to validate the robustness of the model. The conclusions drawn are as follows.

The obtained results indicate that the improved TOPSIS, integrated into the RSSE model in a GIS environment, is apparently appropriate in addressing the problem of land suitability for rural settlements. Suitability evaluation maps obtained using the RSSE model based on traditional TOPSIS and the improved TOPSIS were produced and compared. The improved TOPSIS reduced the effect of correlation among factors, and a reasonable suitability evaluation map was obtained. The criteria weight uncertainty of the RSSE function based on the improved TOPSIS is lower than that of the RSSE function based on traditional TOPSIS, thereby reducing the influence of weight subjectivity derived from expert preference. The resultant maps obtained using the RSSE model can be used to rectify and improve the quality of land use planning. The analysis indicated that a few land

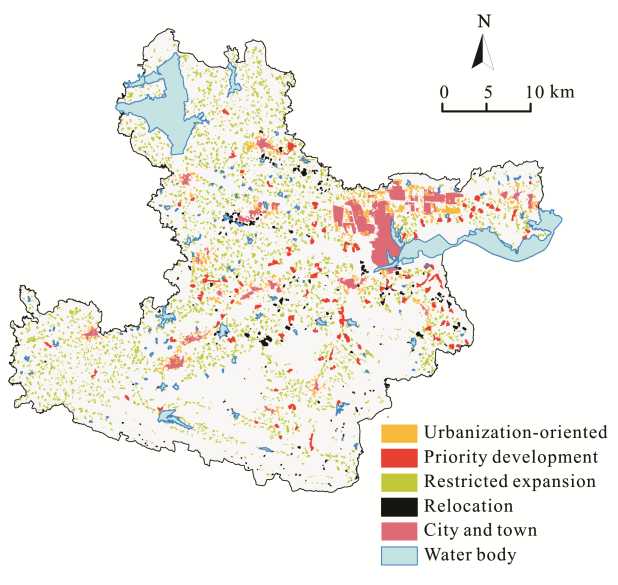

Fig. 9 Distribution of rural settlement patches under different development types

Table 7 Statistics of development strategy for constructing rural settlements

Development strategy	Area (ha)	Population (thousand)	Number of patches
Urbanization-oriented	2057.60	74.25	612
Priority development	1407.79	55.85	103
Restricted expansion	7848.02	272.81	3748
Relocation	537.09	19.29	264
Total	11 850.50	422.20	4727

parcels with planned use conflicted with the suitability map. These land parcels may also require countermeasures in the future. The assessment of rural settlement suitability can help governments design interventions and develop appropriate policies for rural settlements in different locations. The development strategy for each rural settlement patch can provide guidance in terms of the suitability evaluation result and population size. Although this study was conducted in Daye, the employed methodology would also be useful and applicable to other rural areas in China.

The model used in this research simplified the interrelation among factors and regarded it as a trade-off. However, the relationship among factors is unavoidably complementary, and thus, an enhanced model is required. In addition, future iterations of this model should incorporate a wide range of recent and detailed data sets as well as include socioeconomic and infrastructural criteria as data become available.

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