Spatially-explicit sensitivity analysis for land suitability evaluation

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\textbf{Keywords:}
Land suitability evaluation
Multi-criteria decision-making
One-dimensional sensitivity
Spatially explicit analysis
Earth mover’s distance

\textbf{Abstract}

Land suitability evaluation (LSE) is an important step in land-use planning. Using multi-criteria decision-making (MCDM) techniques based on geographic information systems is a flexible and effective approach for this evaluation process. Implementation of sensitivity analysis to validate and calibrate the MCDM can enhance the understanding of the LSE results and assist in making informed planning decisions. The main limitation of sensitivity analysis in MCDM applications is a lack of insight into the spatial dimensions. To address this issue, this paper presents a new framework that incorporates the spatial configuration information from sensitivity analysis for MCDM. The framework consists of a land suitability evaluation and a spatially explicit sensitivity analysis. The sensitivity analysis couples spatial visualization and summary indicators, which include a traditional metric (i.e., the mean of the absolute change rate, MACR) and a novel spatially explicit metric (the Earth Mover’s Distance, EMD). The newly reclaimed region of Yili in China was studied as the representative area. We assumed that the weights were the only source of uncertainty and used a one-dimensional sensitivity analysis. This experiment indicated that the expert LSE results for wheat are robust but relatively sensitive in local areas to changes in the weights. Our results confirm that the MACR and EMD can effectively identify sensitive parameters based on various sensitivity aspects. The EMD explores the new information from the spatial dimensions, which differs from traditional methods for sensitivity analysis. This approach provides a suitable framework based on a spatially explicit sensitivity analysis for the effective implementation of MCDM for robust LSE results.

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\textbf{Introduction}

Agricultural production activities are the foundation of human survival and development. With the growth in the population and the reduction of arable lands, ensuring effective use of arable land to meet the growing demand for food requires rational land use management and planning. Land suitability evaluation (LSE) is an important step in this planning. Because the Food and Agricultural Organization (FAO) recommended an approach for LSE based on climatic, terrain, and soil properties data (FAO, 1976), multi-criteria decision-making (MCDM) techniques have been widely applied to combine information from different criteria for the LSE. The interest of researchers in integrating geographic information systems (GIS) with MCDM has grown steadily (Ceballos-Silva & López-Blanco, 2003; Hussain & Das, 2010; Kumar, Patel, Sarkar, & Dadhwal, 2013; Nisar Ahamed, Gopal Rao, & Murthy, 2000; Pereira & Duckstein, 1993; Tenerelli & Carver, 2012). However, GIS-based MCDM is a multi-disciplinary and multi-step process that can result in many sources of uncertainty (Burman, 2005; Chen, Wood, Linsted, & Maltby, 2011; Wood, Beresford, Barnett, Copplestone, & Leah, 2009), including criteria selection, input data accuracy, standardization method, weight calculation, and aggregation method (Elaalem, Comber, & Fisher, 2011; Reshmidevi, Eldho, & Jana, 2009).

The uncertainties can be classified as aleatory or epistemic (Helton, 1993; Refsgaard, van der Sluijs, Højberg, & Vanrolleghem, 2007). Particularly, the weight assigned to each criterion is one of the most sensitive parameters in MCDM and is a potential source of considerable uncertainty (Larichev & Moshkovich, 1995). For example, the Analytical Hierarchy Process (AHP) (Saaty, 2008) is one of the most popular methods for calculating criteria weights in MCDM via an expert pair-wise comparison matrix (Hossain & Das, 2010; Marinoni, 2004; Ohta et al., 2007; Vaidya & Kumar, 2006). Using their weights, the criteria can be subsequently aggregated into a single imprecise MCDM estimation point, which results in uncertainties with no confidence (Benke, Pelizaro, & Lowell, 2009). Meanwhile, multiple decision-makers are able to set different weights and thus derive a variety of MCDM results for various...
policy targets (Al-Mashrek, Akhir, Rahim, Lihan, & Haider, 2011; Chen et al., 2011; Roura-Pascual, Krug, Richardson, & Hui, 2010). Therefore, the robustness of the LSE results should be evaluated for effective implementation in land-use planning (Fuller, Gross, Duke-Sylvester, & Palmer, 2008; Ligmann-Zielinska & Jankowski, 2008).

For this purpose, use of the uncertainty and sensitivity analysis is helpful in the validation and calibration of MCDM (Delgado & Sendra, 2004; Merritt, Croke, & Jakeman, 2005; Zoras, Triantafyllou, & Hurley, 2007).

Until now, sensitivity analysis has received only minimal attention in previous MCDM studies, although this situation is changing (Chen, Yu, & Khan, 2010; Delgado & Sendra, 2004; Ligmann-Zielinska, Jankowski, & Watkins, 2012; Lowell, Christy, Benke, & Day, 2011). It should be noted that the most critical shortcoming of sensitivity analysis is a lack of insight into the spatial dimensions (Chen et al., 2010; Feick & Hall, 2004). This situation therefore requires spatial visualization techniques and spatially explicit methods applied in the sensitivity analysis to create effective information for the planning decision process, i.e., GIS techniques and simulation algorithms (Ligmann-Zielinska & Jankowski, 2008; Mosadeghi, Warnken, Tomlinson, & Mirfenderesk, 2012; Pannell, 1997). Spatial visualization can display the uncertainties of the evaluation results graphically based on the uncertainty of the input parameters and enhance the experts’ and decision-makers’ understanding of the possible risk in identification of parameter sensitivity in MCDM (Blaser, Sester, & Egenhofer, 2000; Bojórquez-Tapia, Cruz-Bello, & Luna-González, 2012; Chen et al., 2011; Hallisey, 2005; Vitek, Giardino, & Fitzgerald, 1996).

Few studies have attempted to develop a spatial sensitivity analysis for MCDM. Feick and Hall (2004) presented a method for investigating the spatial dimension of the sensitivity of multi-criteria weights. Chen et al. (2010) presented a visualized approach for analyzing the dependency of MCDM output on weight changes and identifying those criteria that are especially sensitive to weight changes in a given spatial dimension. Chen et al. (2011) used an indicator-based method to visually explore the influence of uncertainties on MCDM with the application of the Catchment Evaluation Decision Support System in the Tamar catchment. Ligmann-Zielinska et al. (2012) employed a Monte Carlo simulation and output variance decomposition to represent output uncertainty in spatial form. Tenerelli and Carver (2012) set up a land capability model for assessing the potential of perennial energy crops and performed an uncertainty analysis of the model with a spatial distribution. Ligmann-Zielinska and Jankowski (2012) presented an approach for adjusting the criteria preferences based on distance measures using the explicit consideration of a locational structure.

However, the aforementioned studies focused primarily on spatial visualization of the sensitivity analysis and used traditional statistical methods to summarize the sensitivity results. Traditional methods for calculating the sensitivity indicators of outputs under uncertainty simulation, i.e., change percentage (Maguire, Goodchild, & Rhind, 1991), rank order (Benke, Steel, & Weiss, 2011; Butler, Jia, & Dyer, 1997), standard deviation (Heumann, Walsh, & McDaniel, 2011; Lowell et al., 2011; Pelizaro, Benke, & Sposito, 2011) and cumulative coefficient (Tenerelli & Carver, 2012), consider the outputs of MCDM as discrete and independent elements and ignore the spatial configuration of the evaluation results. Evaluating spatially explicit LSE results in sensitivity analysis requires insight into the spatial information of the sensitivity analysis. Fortunately, the Earth Mover’s Distance (EMD), which is a spatial metric used in image retrieval and histogram comparison (Rubner, Tomasi, & Guibas, 2000), provides an opportunity to consider the spatial dimension of sensitivity analysis.

The objective of this study is to present a new framework that incorporates the spatial configuration information of sensitivity analysis. We evaluated the LSE based on GIS-MCDM with weights calculated using the AHP. The framework examined the sensitivity of different criteria with changes in weights via spatial visualization of the uncertainty outputs and summary sensitivity indicators generated by traditional and spatially explicit methods.

Materials and methods

Study area

The newly reclaimed region located in the valley of Yili lies roughly between 80°22’14” and 83°3’54”E and 43°22’37” and 44°8’22”N (Fig. 1) and is one of seven important land resource development regions established by the Ministry of Land and Resources of the People’s Republic of China. Land resource development engineers aim to achieve a balance of arable lands and improve the land productivity. The Yili River valley, with a better match of soil and water resources, is a limited potential region for land resource development in Western China. Therefore, this region requires effective land-use planning to both combat desertification and improve the quality of newly cultivated lands.

The study area belongs to Yining, Chabuchaer Autonomous County, Huocheng County, and Gongliu County in the administrative region. The region covers an area of ca. 5000 km², with elevations ranging from 661 m to 1572 m and lies within the temperate continental semi-arid climate zone with a mean annual temperature of 8–9 °C, a mean annual precipitation of 200–500 mm, a mean annual evaporation of 1200–1900 mm, and water resources that are the richest in Xinjiang. Land-use types primarily include grassland and farmland with a partial distribution of sand and saline areas. The soil types primarily consist of sierozem with a partial distribution of kastanozem above an altitude of 850 m. Other soil types include
marsh soil, meadow soil, aeolian sandy soil, and small amounts of saline-alkali soil, damp soil, and chernozem soil.

**Methods and data description**

The flowchart (Fig. 2) of GIS-MCDM shows a series of basic steps for implementing spatially explicit sensitivity analysis based on MCDM for LSE. We assumed that the weights were the only source of uncertainty and thus evaluated the sensitivity of the weights alone. Application of our framework based on a raster consists primarily of two stages: land suitability evaluation and sensitivity analysis.

**Land suitability evaluation**

The first stage includes a sequence of evaluated crop selection, relevant criteria selection, criteria standardization, weight calculations, and final aggregation of criteria into the LSE results. Because wheat is the main food crop in Yili, it was chosen for suitability evaluation in our study. Seven criteria related to the wheat suitability evaluation were selected by the authors and experts in Yili, who are familiar with the land-use characteristics and agricultural development of Yili. These criteria are soil texture (ST), soil organic matter (SOM), sand dune waviness (SDW), soil erosion (SE), water supply and drainage (WSD), and groundwater depth (GD). The detailed data sources of the seven criteria are listed in Table 1. Our study team excavated soil profiles and collected soil samples in the study area (Shi, Yang, & Wang, 2009), and soil depth and soil organic matter maps were generated using Kriging interpolation based on the soil sample properties in ArcGIS 9.3 (ESRI Inc., USA). All data were processed and converted to pixels with 300-m resolution in ArcGIS. Each criterion was standardized to four suitability classes, i.e., high suitability, moderate suitability, marginal suitability, and unsuitability, based on the FAO system (FAO, 1976). The classification threshold values of the criteria and the standard scores for the corresponding classes given in Table 2 were obtained from a literature survey and expert opinions. Next, the weights of the criteria were calculated in the AHP by constructing a pair-wise comparison matrix (Saaty, 2008) (Table 3). The scale for the pair-wise comparison in our study ranges from 1 to 9, indicating equal comparison matrix (Saaty, 2008)( Table 3). The scale for the pair-wise comparison in our study ranges from 1 to 9, indicating equal comparison matrix (Saaty, 2008)( Table 3).

The standardized criteria scores were aggregated linearly by weight for the final land suitability evaluation result. The equation used for this is given by:

\[ R = \sum_{i=1}^{n} w_j \times c_i \]  

(1)

where \( R \) is the result of the LSE with a high \( R \) indicating high suitability of the crop, \( w_j \) is the weight of the \( i \)-th criterion from the AHP with \( \sum_{i=1}^{n} w_j = 1 \), \( c_i \) is the standard score of the \( i \)-th criterion, and \( n \) is the number of criteria.

**One-at-a-time method**

In previous studies, two methods were used for simulating the uncertainty of the criteria weights (Feick & Hall, 2004). Monte Carlo simulation is frequently used to generate random criteria weights. However, the subjective assumptions for the parameters of the probability distributions and the normality of the distribution are often subject to bias (Crosetto, Tarantola, & Saltelli, 2000). In contrast, the One-At-a-Time (OAT) method investigates the sensitivities of one-dimensional weights by changing the relative influence of each factor separately, without assumptions. However, this method ignores the interactions caused by modifying the weights of multiple factors simultaneously (Butler et al., 1997). The OAT method estimates the effect on the evaluation results of variation in a single input parameter while holding all other parameters fixed at their nominal values (Daniel, 1958; Rabitz, 1989; Saltelli, Chan, & Scott, 2000). In particular, the weights are determined by experts instead of random selection and are constrained within a certain range. Therefore, the OAT method was used for sensitivity analysis in the second stage of our framework.

The OAT method requires the setting of two parameters, i.e., the range and the step size of the particular weight changes. We assigned a step size of ±5% and a range of ±100%. To ensure that all criteria weights sum to one, the new adjusted weight used for the sensitivity were calculated using the following equation:

\[ \text{WF}(cr) = (1 + cr) \times w_j \]  

(2)

where \( \text{WF}(cr) \) is the particular weight change from the OAT method; \( cr \) is the change rate of the weight, which can be set to
The uncertainty of the simulated results was represented by the change rate. Based on the GIS, the uncertainties of every pixel in the region using all step sizes for a particular weight were spatially visualized in the GIS. Thus, the local area difference visualization of a particular weight with a given change rate could be identified for the sensitivity analysis.

The equation used for the change rate is given as follows:

\[
C_k(w_j, cr) = \frac{R_k (w_j, cr) - R_0}{R_0} \times 100\%
\]  

(5)

where \(C_k(w_j, cr)\) is the change rate of the LSE result with \(w_j\) as a change rate, \(R_k\) is the simulated LSE result for the \(k\)-th pixel, \(R_0\) is the original value of the LSE result calculated by Eq. (1), and \(k\) is the order number of random pixels.

**Summary sensitivity analysis**

For decision-making, summary sensitivity indicators for the entire region were generated by traditional methods (i.e., the mean of the absolute change rate, MACR) and spatially explicit measures (i.e., EMD). High MACR and EMD values indicate high sensitivity.

The MACR was calculated by the following equation:

\[
\text{MACR}(w_j, cr) = \sum_{k=1}^{N} \frac{1}{N} \times \left| \frac{R_k (w_j, cr) - R_0}{R_0} \right| \times 100\%
\]  

(6)

where \(\text{MACR}(w_j, cr)\) is the mean absolute value of the change rate with \(w_j\) as a change rate, and \(N\) is the number of pixels.

The EMD is a distance function used for evaluating the dissimilarity between two histograms and differs from the traditional measures (Levina & Bickel, 2001; Rubner et al., 2000). Based on a solution for finding the minimal cost in a transportation problem, the EMD transforms one histogram into the other (Cha & Srihari, 2002).

Given two histograms \(P\) and \(Q\), the EMD as defined by (Rubner et al., 2000) is:

\[
\text{EMD}(P, Q) = \left( \min_{f_{ij}} \sum_{ij} f_{ij} d_{ij} \right) / \left( \sum_{ij} f_{ij} \right)
\]  

(7)

**Table 2**

Classification threshold values of criteria and standard scores for suitability evaluation of wheat.

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Input dataset</th>
<th>Data source</th>
<th>Format</th>
<th>Processing</th>
</tr>
</thead>
<tbody>
<tr>
<td>ST</td>
<td>Soil type maps of Yili region (1:1000000)</td>
<td>Institute of Geographical Sciences and Natural Resources Research</td>
<td>Polygon</td>
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</tr>
<tr>
<td>SD</td>
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<td>SOM</td>
<td>Topographic maps of Yili region (1:50000)</td>
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**Table 1**

Criteria data sources and processing.

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±5%, ±10%, …… ±100% in our study; and \(w_j\) is the original weight of the \(j\)-th criterion from the AHP. The equation used for the other weights is given as follows:

\[
W_i (cr) = w_j \times \frac{1 - W_i}{1 - w_j}
\]  

(3)

where \(W_i (cr)\) is the other weight adjusted for \(W_i\), i.e., \(i \neq j\); and \(w_i\) is the original weight of the \(i\)-th criterion from the AHP.

Next, 280 LSE results were generated for the sensitivity analysis. The equation used for this calculation is given as:

\[
R(w_j, cr) = W_j \times c_j + \sum_{i \neq j} W_i \times c_i
\]  

(4)

where \(R(w_j, cr)\) is the simulated LSE result with \(W_j\) as the change rate, \(c_j\) is the standard score of the \(i\)-th criterion, and \(c_i\) is the other standard score of the criteria, i.e., \(i \neq j\).

**Local area uncertainty**

The uncertainty of the simulated results was represented by the change rate. Based on the GIS, the uncertainties of every pixel in the region using all step sizes for a particular weight were spatially visualized in the GIS. Thus, the local area difference visualization of

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The EMD has been used in image retrieval (Rubner, Guibas, & Tomasi, 1997; Rubner et al., 2000), comparison of diffusion tensor magnetic resonance images (Jiao et al., 2010), estimation of spatial rainfall distributions (van den Berg, Vandenberghe, De Baets, & Verhoest, 2011), and comparison of priority maps for managing woody invasive alien plants (Roura-Pascual et al., 2010). The values of the original and simulated LSE results are
similar to the gray values of ordinary images. Next, the EMD computations of these two histograms of the LSE maps describe the spatial differences in both, which are similar to the image contrast. A higher EMD value indicates a greater change in the LSE maps. Therefore, we used the EMD as a spatially explicit metric for sensitivity analysis to compare the simulated LSE results with the changing weights and the original results. We used an efficient algorithm (Pele & Werman, 2009) in MATLAB to compute the EMD values.

Results

The standard criteria maps (Fig. 3) were aggregated using weights to create the final land suitability map for wheat in the newly reclaimed region (Fig. 4). The areas that are highly suitable for wheat are primarily located in the southeastern and northeastern regions. In contrast, relatively unsuitable land is located to the west of the region and along the banks of the Yili River with different restrictive suitability factors. The major restrictions on wheat cropping in the northwest are the texture of the sandy soil and low soil organic matter, whereas in the southwestern region, these restrictions include thin soil and low soil organic matter. Soil erosion, water supply and drainage problems, and high groundwater depth restrict wheat cropping along the banks of the Yili River.

Based on the OAT method, the simulated LSE maps for wheat were generated with the weight of each criterion changed from −100% to 100% with a step size of 5%. These simulated uncertainty maps can be used for sensitivity analysis. The MACRs summarize the mean of the absolute change rates for the pixels’ LSE values based on the changing weights (Fig. 5). These values show a linear increase with an increase in the rate of change of the weights but with different gradients for different criteria. The MACRs of the same criteria are almost equal using the same absolute rates of change but with positive and negative values, which indicates similar sensitivities for positive and negative weight changes. A high gradient, which indicates a greater change in the LSE values with the changing weights, indicates high sensitivity of the criterion for LSE. The ranking of the MACRs for all criteria is as follows: SD > ST > SOM > SE > GD > WSD > SDW. The rankings of SD and
ST follow the order of the criteria weights. Similarly, WSD and SDW, which are assigned low weights, are low-sensitivity criteria. The weight of a 75% change is taken as an example. The SD, which is the criterion most sensitive to weight changes, has a MACR of 5.8% if the weight changes by 75%, whereas SDW is the least sensitive criterion with a MACR of just 2.6%. The MACR of the simulated results is significantly lower than the rate of change of the weights (Fig. 5), which indicates that the LSE result is relatively robust.

The rates of change of the LSE values with a 75% change in weight are displayed for spatial visualization in Fig. 6. This figure shows a relatively large spatial variation in the LSE values, which indicates that sensitivity analysis should be carried out. In this situation, the uncertainty maps are displayed for local comparison. For example, the rates of change of all pixels with a 75% change in the SD range from −17.1% to 31.8% are displayed in Fig. 6 and compared with the MACR of 5.8%. Areas with high LSE values are relatively robust, which makes sense because these areas have high values for all criteria scores and are not likely to be affected by a single parameter. However, the areas with relatively low LSE values are more sensitive, especially when the changing weight of the criterion matches the corresponding restrained criterion for these areas. The distribution of sensitivities of different changes in weights is associated with the distribution of suitability classes for the corresponding criterion (Figs. 3 and 6). Taking the SOM map of a weight change by 50% as an example of a locally visualized comparison (Fig. 7), the areas with highly decreased LSE values are generally located where the SOM suitability class is unsuitable. In contrast, the areas with highly increased LSE values have high SOM scores and vice versa (Fig. 7A). In addition, the uncertainty maps of the same criterion with the same absolute change rate but with positive and negative values show a highly similar distribution (Fig. 7A and B). The difference is that the positive and negative LSE values change. This change indicates similar sensitivities in the same pixel for weights with the same changing value, albeit positive and negative.

The EMD was used as a spatially explicit metric in the sensitivity analysis to identify new information from the spatial dimension for LSE. The EMD is a metric that takes both the numerical values and the distribution into consideration. The EMDs show a linear increase with little fluctuation as the rate of change of the weights increases. The change in EMD represents the difference in the numerical LSE values for the same criterion. Therefore, for different criteria, a high gradient indicates high sensitivity. The ranking of the EMDs is SOM > SE > ST > SD > GD > WSD > SDW (Fig. 8), which differs from the ranking of the MACRs. In this situation, GD, WSD, and SDW are the same three criteria with the lowest sensitivity, but the order of the other criteria has changed. This result can be attributed to the spatial distribution of the corresponding criterion. According to Fig. 3, SOM, SE, and ST display a more discrete distribution than that of the others, which may result in greater spatial variations in the LSE values as the weights of the corresponding weights change. Unlike the other criteria that include a highly suitable class, the SOM criterion contains four suitable class areas staggered across the region. This result can explain why the EMD of SOM is the highest out of all criteria, although the MACR of SOM ranks third; it is also the reason why the SE ranks second according to the EMD but ranks fourth according to the MACR. Furthermore, it appears that the SOM has a more staggered spatial distribution than the SE based on the local area difference visualization, which results in the sensitive ranks of these two criteria.

In contrast, SD, which is considered to be the most sensitive parameter according to the MACR, exhibits less sensitivity than the above mentioned three criteria. This observation may be attributed to the fact that the distribution of SD is similar to the distribution in the original evaluation map. However, SDW has the lowest MACR value because the concentrated distribution in the areas of the four suitable classes have the least spatial variation; areas with low-suitability SDW classes are concentrated in the northwest of the region, whereas the other largely contiguous area is highly suitable for wheat. Therefore, the differences in spatial distribution between the LSE maps (which are not easily detected by the local area difference visualization alone but are easily ignored by the traditional metrics) can be explored using the EMD.

Thus, LSE for wheat in our study area is robust yet relatively and locally sensitive to weight changes. This observation should be a warning to experts and multiple decision-makers that the sensitivities of the weights for SD and SOM should be taken into consideration. Careful assignment of these two most sensitive criteria is beneficial for validation of the MCDM and robustness of the LSE results.

**Discussion**

We used the MACR and EMD as different metrics to mine different information from the sensitivity analysis in the LSE. The
MACRs provide information on the numerical changes in the LSE values, indicating the sensitivity of criteria associated with the size of the weights for different criteria. This result is consistent with that of a previous study (Chen et al., 2010). However, the EMDs explore the spatial information between maps, which indicate the sensitivity differences of the criteria primarily attributed to the spatial distribution of the corresponding criteria. Although only a single weight of the criterion is changed and other weights change with equal proportions using the OAT method, the impact of the spatial difference of the criteria propagated on the distinction of final sensitivity is output via the changing weights. This new information from the spatial dimension provided by the EMD cannot be detected by traditional methods (Benke et al., 2011; Butler et al., 1997; Lowell et al., 2011; Maguire et al., 1991; Pelizaro et al., 2011; Tenerelli & Carver, 2012).

To make informed decisions, it is necessary to understand the robustness of the evaluation and have confidence in the decision-making (Chen et al., 2011). Sensitivity analysis can provide useful information for the LSE. In our study, the comparison between the MACR of simulated results and the rate of change of the weights indicates that the LSE for wheat is relatively robust. Spatial visualization shows that areas with high LSE values have low uncertainties, which validates the application of LSE results for land allocation. The relative robustness can be partly attributed to the design of the MCDM because the evaluation results are sensitive to different aggregation techniques (Zanakis, Solomon, Wishart, & Dublish, 1998). The LSE focuses on selection of suitable areas for a given crop for potential land source development (Shi, 1986). The additive model yields a more comprehensive result by combining each criterion and is suitable for the LSE; therefore, this method is always chosen as the aggregation technique in the LSE (Al-Mashreki et al., 2011; Chen et al., 2010; Pelizaro et al., 2011). It makes sense that the additive model is not susceptible to the influence of the individual factors, especially because the weights of the model (range from 0.1 to 0.2) are relatively close in value. The summary sensitivity analysis can provide a straightforward result (i.e., an exact MACR and EMD value in our studies), which decision-makers prefer to use in planning. The MACR with a definite statistical value can be easily understood together with the robustness of the LSE results. However, the question arises as to how the EMD (as a new metric in our study) can provide useful information to assist planners in their decision-making. Similar to other map comparison applications (van den Berg et al., 2011; Jiao et al., 2010; Roura-Pascual et al., 2010), our results show that the EMD can effectively highlight the differences between the simulated land suitability maps and the original map for sensitivity analysis. Different approaches for cataloging uncertainties have resulted in misunderstandings with respect to which uncertainties can be resolved by MCDM (Mosadeghi et al., 2012). Compared with the MACR, the EMD presents a different conclusion with respect to the sensitivity results, which appears to cause confusion for decision-makers.

The EMD explores the spatial information of sensitivities for the LSE from the results. We propose that our framework for sensitivity analysis should integrate these two metrics for the MCDM. Consider the following example using SOM and SD. SOM was considered as the most sensitive factor by the EMD, which means that it causes the largest spatial variation in the LSE values under simulation. These variations in different pixels indicate relative priority changes in the different pixel LSE values, which results in a large contrast in the histograms between the original and simulated LSE maps. Next, these variations are similar to the image contrast and can be detected by the EMD. Furthermore, the priority changes between the pixels’ LSEs cause a decision change for the area selected for wheat cropping. Therefore, the EMD exploration of the spatial sensitivity of LSE with weight changes can assist in land allocation planning. In contrast, SD was considered the most sensitive factor according to the MACR, which indicates a significant value variation in the LSE values under simulation. These variations represent a change in the pixels’ LSE values compared with themselves. However, the priorities of the pixels’ LSE values remain relatively stable when the SD weight changes, which is why the EMD ranked fourth out of all criteria. Therefore, these two metrics, which incorporate different aspects of the information, can be used to detect sensitive parameters in our framework for validation of MCDM.

Application of the EMD requires further study to confirm its validity in sensitivity analysis of the LSE and to investigate its role in supporting decision-making. Although we evaluated only the sensitivity of the weights, the EMD can be applied to other sources of sensitivity (Burgman, 2005; Chen et al., 2011; Reshmidevi et al., 2009; Wood et al., 2009). However, there is no rigorous statistical method for testing whether the LSE maps are significantly different using the EMD. In our study, the EMD can indicate the relative sensitivity of all criteria but cannot determine whether a change in the weight significantly influences the spatial change in the results. Monte Carlo simulation, which is used for significance tests in spatial analysis (Schabenberger & Gotway, 2004), could be a promising approach for improving our method.

Conclusion

A better understanding of the robustness of the LSE results can provide a better aid for its effective implementation in land-use planning. We proposed a framework based on spatially explicit sensitivity analysis using the EMD as a new metric. Application of our framework in the newly reclaimed region of Yili confirmed its effectiveness in the validation of MCDM for LSE. This result indicates that the LSE for wheat is robust according to the MACR, but local areas are relatively sensitive to changing weights according to the spatial visualization. Based on our framework, the MACR summarizes the information in the numerical value variations, whereas the EMD incorporates new information from the spatial variations for sensitivity analysis in the MCDM. In this case, SD and SOM are the two most sensitive criteria in terms of weight changes. These two indicators explore different information with respect to sensitivity and result in different sensitivity orders for the seven criteria. Integration of these two criteria was proposed for validation of MCDM. All the criteria provide a spatially explicit approach for the LSE and informed decision-making. The improvements mentioned above should be incorporated in future studies.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (41071065). We thank Karen Bradshaw in Liwen Bianji (Edanz Group China) for English editing. We are most grateful for the excavation of soil profiles and the collection of soil samples performed by Wang Lixin, Yang Yang, Ma Hanqing, and Zhang Ying.

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