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Integrating remote sensing with GIS-based multi-criteria evaluation approach for Karst rocky desertification assessment in Southwest of China

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Abstract. The increasing exploitation of Karst resources is leading to severe environmental impacts, as Karst frequently occurs in the most fragile and vulnerable environments. This paper presents a multi-criteria evaluation (MCE) approach in a spatial context to support Karst rocky desertification (KRD) assessment by integrating remote sensing data with GIS. The study area is located in Wenshan Prefecture, Yunnan Province, Southwest of China. Criteria and impact factors for KRD first were identified and weighted through pairwise comparison method. A GIS fuzzy set membership function was then used to generate gradient effects of each criterion, and a clustering method based on K-mean algorithms was used to classify KRD into several descending rank zones (or levels). Both ROC and error matrix assessments indicated that the MCE approach is better than the NDVI approach. In addition, we found it is useful to integrate the topographic and human disturbance factors into KRD mapping and assessment, compared with most of the previous KRD assessment studies mainly focused on developing vegetation or land cover information in karst regions by using remote sensing alone. Furthermore, the integrated MCE approach is robust, flexible, and easy to be implemented. It also explicitly includes the quantitative and qualitative information, for instance, opinions of decision makers and experts as well as characteristics of the landscape.

1. Introduction

Karst is characterized by the predominance of rock dissolution over mechanical erosion, and is typical for present temperate (cold and warm) and tropical environments [1-2]. In the Southwest of China, the size of Karst landscapes is up to half million km^2, largely located in Yunnan, Guizhou and Guangxi provinces [3-4]. It represents one of the world's most spectacular examples of humid tropical to subtropical karst landscapes. It also is one of the most severe ecological and environmental issues in China [5]. Accurately mapping and assessing karst rocky desertification (KRD) is crucial for the understanding of the dynamics of the Karst landscapes, and thus can provide insights for sustainable planning and management practices aimed at preserving essential ecosystems functions [6].

Previous studies mainly focused on developing linkages between spectral response and surface features of karst systems (such as vegetation and non-vegetation covers) by using remote sensing [7-9]. Karst systems are extremely complex and affected by human activities and biophysical ecological process [2, 6-7]. Various studies have shown the importance of topography and human disturbance on KRD [7, 10-13]. Thus, incorporating the topographic and human disturbance factors with remote sensing data (i.e. vegetation indices) into KRD assessment might be beneficial. The objective of this study is to present a conceptual framework for assessment of current status and future projection of KRD. With this framework, we attempt to provide an approach that helps link KRD assessment to

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regional planning. MCE approach is a formal approach to address a problem in a structured way [14]. Thus, data of driving forces can be applied in an aggregation framework allowing for an examination of the initial problem [15-16]. Therefore, we aim to present a methodology that integrates remote sensing data with GIS using a MCE approach in a spatial context to support KRD assessment. We use Wenshan prefecture in the Yunnan Province, China as a case study. Vegetation and non-vegetation cover information derived from satellite image data will be used by weighting the multi-criteria in the spatial analysis. Hence, the approach of this study should be applicable to the whole Southwest of China, as well as elsewhere in the world.

2. Material and methods

2.1. Study area

The study area is located in Wenshan Prefecture, Yunnan Province, Southwest of China (22°43′—23°56′N， 103°37′—105°23′E (Figure 1). It represents the typical limestone karst landscape in Yunnan Province. It east neighbors to Guangxi Province, and south borders the Socialist Republic of Vietnam. 70% areas of the Prefecture belong to sub-tropical area, and 30% is tropical area. Wenshan Prefecture is home to the richest biological and ethnic diversity in China. More than 20 ethnics are living there. The maximum altitude range is about 2900 meters. The climate of the region is strongly seasonal. The yearly average temperature is about 19ºC, and yearly rainfall is about 779 mm.

Figure 1. Location of the study area.

2.2. Experimental data

The TM image was acquired on September 25, 2007 with a sun elevation of 58.38° and solar azimuth angle of 130.35°. In addition, the 25 meter resolution DEM data produced by the China State Bureau of Surveying and Mapping was made available for this study (http://www.sbsm.gov.cn/). Digital geographical data, including administrative boundaries, hydrology, roads, villages, and towns, were collected from different government departments. To be consistent with the resolution of the image data, all data were converted into raster format with a 30-m grid size in a GIS environment (IDRISI Taiga). Field survey (August to September 2012) was carried out to establish the main characteristics and variability of the KRD, and to acquire reliable field data for evaluating the accuracy of the KRD assessment results.

2.3. Methods

MCE is a powerful tool for supporting complex decision making by combining a set of criteria. Remote sensing was combined with GIS-based MCE method to evaluate KRD, in which a stepwise process was used to identify KRD degrees. The process included 4 steps: 1) criteria for the objective were defined; 2) the degree of KRD map was made; 3) using cluster analysis, the degree of KRD map was classified into several zones corresponding to different KRD levels; and 4) finally, the combination MCE approach was compared to NDVI method by using receiver operating characteristic (ROC) analysis and accuracy assessment.

3. Results

3.1. ROC evaluation

ROC statistic is the area under curve (AUC) that connects the plotted points. An AUC value of 1 indicates that there is perfect spatial agreement between the reference map (i.e., validation data) and the suitability map (i.e., the predicted image). An AUC value of 50% is the agreement that would be expected due to chance (e.g., if the predicted image values were assigned to random locations). The ROC works for exactly two land types. If the maps have more than two land-cover types, they should be reclassified into the category of interest versus other, then each category can have its own ROC [17].

Table 1. Summary of AUC values for each KRD class derived by four KRD assessment approaches.

Code	KRD assessment strategies	High KRD (AUC)	Middle KRD (AUC)	Low KRD (AUC)	No KRD (AUC)
MCE1	MCE using remote sensing criteria	96.4%	70.8%	76.1%	94.6%
MCE2	MCE using remote sensing and topographic criteria	95.8%	71.1%	76.0%	93.9%
MCE3	MCE using remote sensing, topographic, and human disturbance criteria	96.2%	67.8%	75.7%	94.0%
NDVI	NDVI	94.7%	59.8%	64.7%	88.6%

In this study, the KRD has been classified into four levels. The ROC curves show that the high level of KRD can be accurately predicted by all of the four KRD mapping strategies (Figure 2 and Table 1). The lowest AUC value of 94.7% was obtained by using NDVI (Table 3). This also was true for the no KRD class (Figure 2D and Table 1). The no KRD with an AUC of 88.6% obtained by NDVI is much lower than other KRD mapping strategies (Table 3). The ROC also show that AUC values of middle and low levels of KRD are much lower than high KRD and no KRD (forests) (Figures 2 and Table 1). Particularly, ROC curves clearly show that AUC values derived by NDVI are much lower than other MCE approaches (Table 1). However, the AUC values for each KRD class obtained by the three MCE approaches are very similar (Table 2). The t-test also showed that the ROC true positive rate derived by NDVI is significantly lower than other three MCE approaches (Table 2).

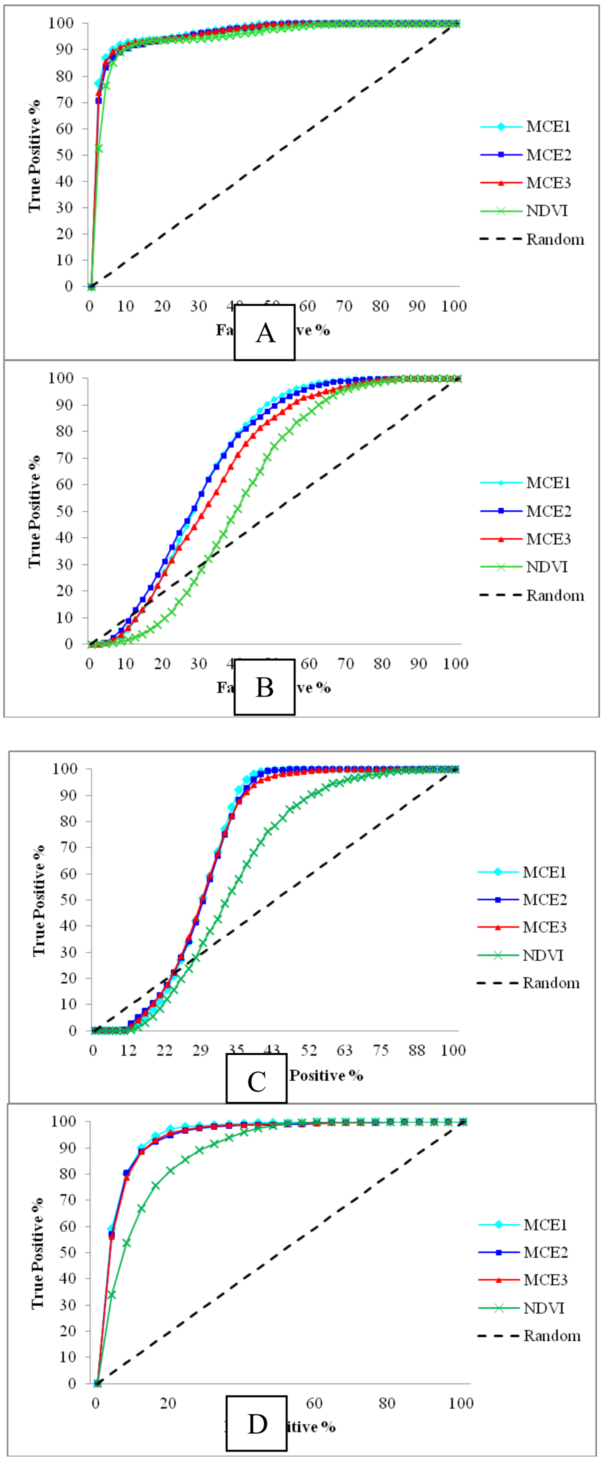

Figure 2. ROC curves to validate modes of high level KRD (A), middle level KRD (B), low level KRD (C), no KRD (D) using five maps based on: random location (bottom ROC = 50%), MCE approach using remote sensing criteria (MCE1), MCE approach using remote sensing and topographic criteria (MCE2), MCE approach using remote sensing, topographic, and human disturbance criteria (MCE3), NDVI approach.

Table 2. Pair-wise t-test of the comparisons of ROC true positive rate derived by the different KRD assessment approaches.

KRD classes	MCE1 vs MCE2	MCE1 vs MCE3	MCE1 vs NDVI	MCE2 vs MCE3	MCE2 vs NDVI	MCE3 vs NDVI
High KRD	3.298**	2.78**	3.153**	-3.4***	2.903**	3.204**
Middle KRD	-1.185	6.099***	7.11***	8.068***	7.319***	6.938***
Low KRD	0.662	1.749	6.061***	2.021*	6.531***	6.501***
No KRD	4.692***	4.556***	3.348**	-0.758	3.123**	3.227**

***p<0.001, **p<0.01, *p<0.05, n = 51

3.2. Accuracy assessment

Table 3 presents the overall accuracies and the Kappa values of the different KRD mapping strategies. The NDVI approach had the lowest accuracy. The highest accuracy was obtained by MCE using remote sensing, topographic, and human disturbance criteria. The Z values showed that accuracies could be significantly improved by MCE approach (Table 4). In addition, the accuracy is significantly higher using topographic and human disturbance criteria (MCE2 and MCE3), compared to that only using remote sensing criteria (MCE1) (Table 3). However, there is no significant difference between the approach using MCE2 (excluding human disturbance factors) and that using MCE3 (including human disturbance factors) (Table 4). It indicated that including human disturbance factors did not significantly improve the accuracy of the approach (Table 4).

Table 3. Summary of the KRD assessment results derived by four different approaches.

Code	KRD assessment strategies	Overall accuracy (OA) (n = 25038)	Kappa (n = 25038)
MCE1	MCE using remote sensing criteria	81.58%	0.6547
MCE2	MCE using remote sensing and topographic criteria	83.51%	0.7047
MCE3	MCE using remote sensing, topographic, and human disturbance criteria	84.75%	0.7258
NDVI	NDVI	68%	0.3972

Table 4. Pair-wise Z statistic test of the comparisons of the different KRD assessment methods.

Pair-wise	Z value	Pair-wise	Z value	Pair-wise	Z value
MCE1 vs MCE2	-2.55**	MCE1 vs NDVI	15.75***	MCE2 vs NDVI	17.98***
MCE1 vs MCE3	-3.54***	MCE2 vs MCE3	-1.02	MCE3 vs NDVI	18.61***

***p<0.001, **p<0.01, *p<0.05

4. Conclusions and future work

This paper proposed a remote sensing combined with GIS-based MCE approach for KRD assessment. They offer the possibility to use. Overall, the pilot process worked well as the degree of KRD map. Both ROC and error matrix assessments indicated that the combination of remote sensing with GIS-based MCE approaches is better than the NDVI approach. In addition, we found it is useful to integrate the topographic and human disturbance factors into KRD mapping and assessment, compared with most of the previous KRD assessment studies mainly focused on developing vegetation or land covers information in karst regions by using remote sensing alone. Furthermore, the combined MCE approach is a robust and flexible method that is easily implemented and explicitly includes the quantitative and qualitative information as obtained; for instance, opinions of decision makers and experts as well as characteristics of the landscape. We present a scientifically sound and practical KRD mapping and assessment approach that can be used to enhance regional management schemes of KRD or other environmental issues and applied to regional sustainable planning for development in China or in other developing countries that have similar environmental issues.

Previous studies have reported that soil and geology conditions are also very important for KRD. Therefore, the soil and geology data would be included in the combination MCE approach for KRD mapping and assessment in future. As mentioned above, accurately mapping and assessing KRD is important for quantifying past changes and also in predicting future changes, and can help to elaborate sustainable planning and management practices aimed at preserving essential ecosystems functions. Future work will also focus on the KRD change quantification and assessment.

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