Remote sensing of indicators for evaluating karst rocky desertification

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Abstract: Karst rocky desertification is the most serious problems of land degradation in karst regions, southwest China. Remote sensing technique is the promising method to assess and monitor the degree and extent of karst rocky desertification at large scale. In this study, based on field spectral reflectance measurements, the traditional vegetation indices (VIs) and linear spectral unmixing (LSU) are assessed to extract the key indicators of karst rocky desertification. Karst rocky desertification synthesis index (KRDSI) has been developed with the unique of spectral features observed in non-vegetation land cover types. The results show that VIs could be used to extract the fractional cover of green vegetation, and they are not sensitive to soil background. Both VIs and LSU can efficiently extract the fractional cover of non-green vegetation. Compared with LSU, KRDSI shows more consistent results with the field measurement of non-vegetation land cover fractions. This study indicates that evaluation indicators of karst rocky desertification can be extracted from the Hyperion image with the combination of vegetation indices and KRDSI values.

Key words: spectral indices, linear spectral unmixing, KRDSI, karst rocky desertification

1 INTRODUCTION

Karst regions in southwest China are in the central karst geomorphology of eastern Asia and are one of the largest karst areas in the world with 540000 km². For the actively biological and chemical processes of CO₂-H₂O-CaCO₃ system, karst regions are typically ecological fragile zones constrained by geological setting and are sensitive to global changes (Yuan, 1999; Liu, et al., 2009). The region belongs to subtropical monsoon and wetness climate. Vegetation, soil and rock in karst regions are cross-distributed and the soil is not continuous, resulting in high spatial and temporal heterogeneity. Compared with non-karst regions, vegetation distributed in karst regions has unique characteristics of rocky and dry standing conditions. Karst rocky desertification, with severe soil erosion and exposed bedrock, is the typical land degradation in karst regions for the combination of fragile eco-geological setting and unreasonable land use (Ju, et al., 2006; Wang & Li, 2007).

Because of the inherent merits of macro scale, frequency, efficiency, and synthesis, remote sensing is a promising tool to monitor and assess karst rocky desertification. The traditional methods for remotely sensed monitoring karst rocky desertification need to firstly establish the evaluating indicators, their ranges, and the classification symbols. Then, they enhance the display characteristics through bands combinations. Finally, they focused on visual interpretation and computer-assisted digital processing of aerial photographs and satellite images. These methods are highly subjective and low efficient, and might result in significant errors. In addition, it could also lead to low precision when comparing different regions using extracted information of karst rocky desertification (Yue, 2010).

There are still no standard for classifying karst rocky desertification (Wang, et al., 2004; Wang & Li, 2005; Ju, et al., 2006).
Therefore, it should take the characteristics of remote sensing technique in consideration and combine the needs of applications when monitoring karst rocky desertification with remote sensing. Remote sensing is a tool that can be used to provide the qualification of ecological indicators for assessing karst rocky desertification. On one hand, karst rocky desertification is a kind of landscape similar to desertification and the rate of exposed bedrock and fractional cover of vegetation are the main surface symbols and key evaluating indicators of karst rocky desertification. On the other hand, karst rocky desertification is also a dynamic process of land degradation and is the integration of all land cover types. For the effects of seasonal changes, the fractional cover of non-photosynthetic vegetation and bare soil are also the key factors of karst rocky desertification. Therefore, it needs to take multiple cover types of land surfaces in consideration of evaluating karst rocky desertification. Vegetation indices, which are designed according to the spectral features of green vegetation, could be used to extract the information of vegetation. There are no spectral indices available now, however, could be used to indicate the extent or degree of karst rocky desertification. Therefore, it needs to explore the methods for the extraction of evaluation indicators of karst rocky desertification in complicate environment.

Based on the measurement and analysis of complex spectral features of different extent of karst rocky desertification, this study firstly validates the use of the main existing methods for extraction fractional cover of land surfaces to acquire evaluation indicators of karst rocky desertification, and then explores the spectral features of evaluating indicators of karst rocky desertification and designs new spectral indices that could be directly used to quantify evaluating indicators of karst rocky desertification. At last, we examine the new spectral indices with EO-1 Hyperion image.

2 MATERIALS AND METHODS

2.1 Spectral measurement

The spectra of different extent karst rocky desertification are simulated with field spectral measurement and the effects of topography, shadow, and solar altitude on spectra are not taken into consideration. The sites are located in Huanjiang Experimental Station of Karst Ecosystem, Chinese Academy of Sciences, which is the only national ecosystem observation in karst regions currently, southwest China. The multi-annual temperature is 16.5°C—20.5°C and precipitation is 1389.1 mm/year. The main vegetation types are shrub and grass with rocky and dry standing conditions. A total of 91 randomly distributed samples were collected. Each sample covered relatively homogeneous vegetation and contained different proportions of PV, NPV, bare soil and exposed bedrock. For the limits of equipment, we mainly collected the spectra of shrub and grass.

The spectrum was measured using an Analytical Spectral Devices (ASD) FieldSpecFR spectrometer in a range of 350—2500 nm, and the spectral sampling interval was 1.4 nm between 350 nm and 1000 nm and 2 nm between 1000 nm and 2500 nm. A black colored circle frame was placed to mark the area observed. The spectrometer aperture with a field-of-view of 25° was held 1.5m above the land surface in the nadir-viewing position, thus measuring an estimated circle with radius of 33 cm (Fig. 1). Each sample was also photographed with a digital camera. To estimate the proportion of PV, NPV, bare soil and exposed bedrock, circle frame was clipped using Adobe Photoshop software. The fractional cover of main land cover types were acquired with K-Means unsupervised classification. The values of PV, NPV, bare soil and exposed bedrock pixels were then calculated using a program coded in Interactive Data Language (IDL).

![](Fig.1 Illustration of the spectral measurement)

2.2 Choice and extraction of spectral features

The field measured spectra could provide abundant spectral information. However, the increase of bands would result in redundant information and thus augment the complexity of data processing. Therefore, it needs to reduce and optimize the spectral dimension information. The selection and extraction of spectral features are the two methods to decrease the spectral dimension information (Tong, et al., 2006). The selection of spectral features can accentuate the most unique spectral bands, while the extraction of spectral features can represent the spectral parameter of specific property or distinguish from other materials. In this study, tied-spectrum transform, a spectral normalization method that subtracts the reflectance value at one wavelength (the tie point) from all other wavelengths, was used to accentuate the differences of spectral absorption features of land cover types of interest, and to exploit the diagnostic spectral shapes of each land-cover type (Lobell & Asner, 2001):

\[ \rho' = \rho - \rho_0 \]  

where \( \rho' \) is the tied-spectrum spectral reflectance, \( \rho \) is the original spectral reflectance, and \( \rho_0 \) is the spectral reflectance of the tie-point wavelength \( t \).

2.3 Methods of remotely sensed inversion of fraction of land surface

The changes of eco-environment lead to the variations of land surface coverage, to some extent, it can reflect the eco-environmental conditions (Hill, et al., 1995; Huete, et al., 2003). Besides the visual interpretation, vegetation indices and spectral unmixing analysis are the widely used methods to extract land surface coverage information using remote sensing (Camacho-De Coca, et al., 2004; Guerschman, et al., 2009; Gill & Phinn, 2009). However, there are few studies on the extraction of karst rocky desertification with vegetation indices or spectral unmixing analysis. There are needs to examine the validation of these two combined methods
for directly extracting karst rocky desertification. We choose three types of vegetation indices to extract karst rocky desertification: (1) Indices based on the normalized difference: the Simple Ratio Vegetation Index (RVI) and the Normalized Difference Vegetation Index (NDVI); (2) Soil-line vegetation indices: Soil-Adjusted Vegetation Index (SAVI) and Modified Soil-Adjusted Vegetation Index (MSAVI); and (3) Indices based on discrete bands: Triangular Vegetation Index (TVI) and Modified Chlorophyll Absorption Ratio Index (MCARI) (Van der Meer, 2004; Haboudane, et al., 2004).

In addition, for the comparison of ability of broad-band and narrow-band vegetation indices used to extract karst rocky desertification, we convolved the field measured spectra to broad-band MODIS and TM according to their spectral response functions:

\[ \rho_i(\lambda) = \frac{\sum E(\lambda) r_i(\lambda) \psi(\lambda) \Delta \lambda}{\sum E(\lambda) \psi(\lambda) \Delta \lambda} \]  

where \( \rho_i(\lambda) \) is the simulated reflectance of broad-band satellite, \( n \) is the number of points of spectral response function in broad-band range, \( \psi(\lambda) \) is the reflectance of object at \( i \)th responding band by spectrometer, \( E(\lambda) \) is the radiance of whiteboard at \( i \)th responding band by spectrometer (W·m\(^{-2}\)·sr\(^{-1}\)·nm), namely incident solar radiance, \( \psi(\lambda) \) is the values of spectral response function of different satellite sensors at \( i \)th band, \( \Delta \lambda \) is the interval of spectral response band. For the spectral unmixing analysis, we used ‘sum to 1’ partly constrained linear spectral unmixing method (Sabol, et al., 2002), and compared with the performance of new designed spectral index when employed to extract karst land cover information.

### 2.4 Design of karst rocky desertification synthesis index

The performance and the suitability of a particular index are generally determined by the sensitivity of the index to the characteristics of interest. The spectral features of NPV, exposed carbonate rocks, and bare limestone soil show significantly difference in the short-wave infrared (SWIR 2000—2400 nm) ranges in the karst environment (Yue, et al. 2010). Additionally, the presence or absence of water and hydroxyl, carbonate and sulphate determine the absorption features in the SWIR region (Van 2004). Therefore, we aim to design a new spectral index to extract land cover information according to the spectral features of NPV, soil, and rock in SWIR region. A series of spectral variables in SWIR are employed to describe or capture the spectral absorption features. These spectral parameters are called karst rocky desertification synthesis index (KRDISI), and pre-study showed that the KRDISI, which was used to describe the absorption depth, could be directly used to extract non-vegetation fractional coverage (Yue, et al., 2010):

\[ \text{KRDISI} = \rho_0 - \rho_i \]

where \( \rho_i \) is the sample spectral reflectance at wavelength \( c \) of the SWIR; \( a, b \) and \( c \) are the wavelengths of the two shoulders and the peak absorption, respectively; and \( \rho_0 \) is the estimated reflectance at wavelength \( c \), assuming there were no absorption features present and therefore interpolating linearly between the reflectance at wavelengths \( a \) and \( b \) (Fig. 2).

### 3 RESULTS AND DISCUSSION

#### 3.1 Spectral features of symbols of karst rocky desertification

Referenced the methods for monitoring land desertification (GB/T20483-2006) and evaluating means of desertification (Gao, et al., 1998), we establish the fraction of PV, NPV, exposed bedrock, and bare soil as the key remotely sensed evaluation indicators of karst rocky desertification with the combinations of main existing classifications of karst rocky desertification (Wang & Li, 2005; Yue, 2010) and inherent merits of optical remote sensing. Compared
with the distinguishing spectral features of PV, the spectral differences of NPV, bare soil and exposed bedrock are relatively small, especially in the visible range. In the short-wave infrared (SWIR 2000—2400 nm) spectral range, the spectral differences may be identified, although they are not evident. However, after the tied-spectrum transform, the differences of spectral absorption features of NPV, soil and rock are accentuated and their diagnostic spectral absorptions are apparent (Yue, et al. 2010).

3.2 Reasons for the spectral differences of symbols of karst rocky desertification

For PV, its spectral features are significantly different from other land cover types due to the chlorophyll absorption that results in low reflection in the visible spectral regions and the leaf tissues lead high reflection and transmission in short-wave bands. For NPV, soil and rock, their spectral features are different in SWIR. Fig. 4 shows the tied-spectra of NPV, soil and rock and is equally interval.

For the performance of different types of vegetation indices, TVI is the best to assess vegetation fraction, while the most widely used NDVI does not perform well. It is due to the saturated problems of NDVI for the vegetation fraction higher than 60%, and the NDVI is almost insensitive to vegetation fraction changes (Gitelson, et al., 2002). The performances of SAVI and MSAVI, that consider the effect of background soil, are not much better than TVI and NDVI. So, it suggested that it might be not taken the effects of soil when using vegetation indices to extract vegetation fraction since that the soil is thin and is not continuously distributed in karst regions.

By the comparison of the performance of broad and narrow band vegetation indices, the results show that the narrow band vegetation indices are better than broad band vegetation indices (Table 1 and Table 2). The narrow band MCARI, which could describe the chlorophyll absorption, performs much better than broad band MCARI. This indicates that narrow band could capture the absorption features that broad band could not. It also proves the

Table 1 Linear regression of hyperspectral vegetation indices and fractional cover of photosynthetic vegetation

<table>
<thead>
<tr>
<th>Spectral Parameters</th>
<th>Linear Regression</th>
<th>r²</th>
</tr>
</thead>
<tbody>
<tr>
<td>RVI</td>
<td>y=1.25x-14.88</td>
<td>0.79</td>
</tr>
<tr>
<td>RVI_broad</td>
<td>y=1.28x-0.32</td>
<td>0.78</td>
</tr>
<tr>
<td>NDVI</td>
<td>y=-1.84x-0.18</td>
<td>0.79</td>
</tr>
<tr>
<td>MSAVI</td>
<td>y=1.79x-0.13</td>
<td>0.79</td>
</tr>
<tr>
<td>TVI</td>
<td>y=-0.05x-0.04</td>
<td>0.82</td>
</tr>
<tr>
<td>MCARI</td>
<td>y=7.32x+0.00</td>
<td>0.81</td>
</tr>
</tbody>
</table>

Table 2 Linear regression of broad vegetation indices and fractional cover of photosynthetic vegetation

<table>
<thead>
<tr>
<th>Spectral Parameters</th>
<th>Linear Regression</th>
<th>r²</th>
</tr>
</thead>
<tbody>
<tr>
<td>RVI_broad</td>
<td>y=0.13x-0.18</td>
<td>0.79</td>
</tr>
<tr>
<td>RVI</td>
<td>y=0.15x-0.19</td>
<td>0.78</td>
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<tr>
<td>NDVI</td>
<td>y=1.31x-0.30</td>
<td>0.78</td>
</tr>
<tr>
<td>MSAVI</td>
<td>y=1.35x-0.34</td>
<td>0.77</td>
</tr>
<tr>
<td>SAVI</td>
<td>y=1.96x-0.23</td>
<td>0.78</td>
</tr>
<tr>
<td>SAVI_broad</td>
<td>y=1.99x-0.27</td>
<td>0.77</td>
</tr>
<tr>
<td>MSAVI_broad</td>
<td>y=1.91x-0.18</td>
<td>0.78</td>
</tr>
<tr>
<td>TVI</td>
<td>y=0.05x-0.13</td>
<td>0.81</td>
</tr>
<tr>
<td>TVI_broad</td>
<td>y=0.05x-0.15</td>
<td>0.80</td>
</tr>
<tr>
<td>MCARI</td>
<td>y=0.43x+0.07</td>
<td>0.69</td>
</tr>
<tr>
<td>MCARI_broad</td>
<td>y=0.42x+0.06</td>
<td>0.69</td>
</tr>
</tbody>
</table>

Fig. 4 Reasons for spectral differences of NPV, soil and rock

The NPV spectrum shows that the absorption features are mainly in the short-wave spectral region near 2100 and 2300 nm, which are dominated by cellulose and lignin spectral features (Curran, 1989). The bare soil shows a characteristic clay feature near 2200 nm and a carbonate spectral typical feature near 2330 nm (Ben-Dor, et al., 1999; Chabrillat, et al., 2004). In the exposed bedrock, an absorption feature near 2350 nm and a double absorption features near 2200 nm are often identified for carbonate rocks of karst regions and clay-rich rocks, unlike the bare soils, where smectite is usually the type of clay detected as smectite has a single absorption near 2200 nm (Fu, 1996; Chabrillat, et al. 2004).

3.3 Validation of broad and narrow band vegetation indices

The linear regression of broad and narrow band vegetation indices with the fractional cover of vegetation are shown in Table 1 and Table 2. The results show that both broad and narrow band vegetation indices have high linear regressions with vegetation fraction with high coefficients of determination r² values. The reason is that the vegetation indices are designed based on the unique spectral features of green vegetation, which have two absorption valleys in 0.5–0.7 μm and reflectance is lower than 20%, while the relatively higher reflectance due to leaf tissues. The high r² between vegetation indices and vegetation fraction indicates that vegetation indices can be directly used to assess vegetation fraction, especially for the indices based on narrow discrete bands that can describe the chlorophyll absorption, which is not observed for broad bands.
advantages of narrow band vegetation indices compared with the corresponding broad band ones. However, none of the vegetation indices can be effectively and directly used to extract the fraction of NPV, soil and rock.

3.4 Validation of linear spectral unmixing analysis

Linear spectral unmixing analysis (LSU) could be effectively used to extract the vegetation fraction, however it could not work well for the extraction of soil fraction ($r^2=0.54$). Additionally, LSU can not be used to extract the fraction of NPV and rock (Fig.5 (a) (b(c)). The reasons are as follows. Firstly, we use the average filed spectral reflectance as an endmember, while the spectra are different for different or intra-types, especially for different carbonate rocks (Fu, 1996). Secondly, the weathering processes also result in spectral changes of carbonate rocks. Thirdly, the linear mixing model holds when the mixing scale is macroscopic (Nash & Conel, 1974), whereas the nonlinear model holds when the mixing scale is microscopic (Singer, 1981). The combinations of incident solar radiation scattering and shadow make extraction of karst rocky desertification undesirable. Therefore, LSU can be of potential to extract the vegetation fraction, but could not directly be used for the extraction of non-vegetation fraction.

3.5 Validation of KRDSI

The linear regressions of KRDSI, with the fractional cover of NPV, soil and rock are shown in table 3. For NPV, $KRDSI_{NPV}$, that capture the absorption depth of cellulose and lignin, are well linear with NPV fraction ($r^2=0.70$). It indicates that the higher of NPV fraction, the more prominent absorption features. So, it could be used the extent of absorption features to deduce soil fraction. $KRDSI_{soil}$, which describes the absorption depth of limestone, is well linearly correlated with soil fraction, with the highest $r^2$ of 0.73.

The rate of exposed bedrock is the key indicator of karst rocky desertification. Up to now, there is no effective method for effectively calculating this for the high complexity and heterogeneity in karst environments. Carbonate rocks are the foundation of karst, mainly including limestone and dolomite. The $\text{CO}_3^2-$ central wavelength of absorption features of dolomite is near 2300 nm, while that of limestone is near 2340 nm, indicating that the central wavelength will move toward longer wavelengths with the increase of dolomite (Fu, 1996). Therefore, combined with the weathering processes of carbonate rocks (Younis, et al., 1997), the variation of absorption features will result increasing in the difficulty of calculating exposed bedrock. Thus, it leads to the lower linear relationship between KRDSI and rock fraction with lower $r^2$ of 0.55.

3.6 Comparison between KRDSI and LSU

Limestone soil is widely distributed in karst regions. The bare limestone soil shows a clay feature near 2200 nm, and similarly, it could be used the extent of absorption features to deduce soil fraction. $KRDSI_{limestone}$, which describes the absorption depth of limestone, is well linearly correlated with soil fraction, with the highest $r^2$ of 0.73.

Table 3 Linear regression of fraction of non-photosynthetic vegetation, carbonate rocks and limestone soil and KRDSI

<table>
<thead>
<tr>
<th>Spectral indices</th>
<th>Linear regression</th>
<th>$r^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>NPV KRDSI$_{NPV}$</td>
<td>$y=23.73x+0.21$</td>
<td>0.70</td>
</tr>
<tr>
<td>Soil KRDSI$_{soil}$</td>
<td>$y=38.74x+0.22$</td>
<td>0.73</td>
</tr>
<tr>
<td>Rock KRDSI$_{rock}$</td>
<td>$y=18.24x+0.08$</td>
<td>0.55</td>
</tr>
</tbody>
</table>

Table 3 Linear regression of fraction of non-photosynthetic vegetation, carbonate rocks and limestone soil and KRDSI.

3.7 Extraction of evaluation indicators of karst rocky desertification with remote sensing

For the confirmation of the advantages of KRDSI, we compare the performance between KRDSI and LSU for extracting the symbols of karst rocky desertification (Fig. 5). For NPV, the $r^2$ of linear regression between KRDSI inverse NPV fraction and surveyed NPV fraction is 0.70, while only 0.33 is observed for LSU. KRDSI has the higher $r^2$ both for the rock and the soil fraction extraction. It demonstrates that KRDSI holds the potential to estimate the fractional cover of NPV, bare soil and exposed bedrock. However, the estimated proportions of exposed bedrock are not so accurate. Possible reason is the different types and the weathering processes of carbonate rocks which result in variability of spectral absorption features.

Fig.5 Comparison the performance between KRDSI and LSU to extract the symbols of rocky desertification (Yue, et al. 2010)
fectively estimated with hyperspectral images based on the combinations of vegetation indices and KRDSI. We further validate this strategy with EO-1 Hyperion image, which covers a typical karst rocky desertification area near Qibainong, Dahua County, Guangxi Province. Mixed pixels are severe for the high heterogeneity of karst environment. Therefore, we use field surveyed points to validate the accuracy of extraction of evaluation indicators of karst rocky desertification with Hyperion. A total of 21 effective points are collected and the results of validation are shown in Table 4. The results suggest that the evaluation indicators of karst rocky desertification can be extracted relatively simply with the combinations of vegetation indices and KRDSI.

Table 4 The coefficient of determination $r^2$ and cross-validation RMSE of linear relationship between surveyed and extraction from Hyperion fractional cover of PV, NPV, Soil and Rock.

<table>
<thead>
<tr>
<th></th>
<th>PV</th>
<th>NPV</th>
<th>Soil</th>
<th>Rock</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r^2$</td>
<td>0.9058</td>
<td>0.6828</td>
<td>0.7173</td>
<td>0.5295</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.0470</td>
<td>0.0593</td>
<td>0.0390</td>
<td>0.1059</td>
</tr>
</tbody>
</table>

4 CONCLUSIONS

Karst regions in southwest China have been reported to possess severe land degradation of karst rocky desertification. Following sandy desertification in northwest China and soil and water loss in the loess plateau, karst rocky desertification is considered to be one of the most destructive ecological and environmental problems in China. The government is paying more attention on the ecological and environmental problems of karst rocky desertification, especially with the implementation of Program for General Treatment of Karst Rocky Desertification (2006—2015). It needs to quickly and accurately acquire the information of karst rocky desertification which results in new challenges to applications of remote sensing in monitoring karst rocky desertification. Based on the filed spectral measurement and EO-1 Hyperion image, this study aims to develop new methods for extracting evaluation indicators of karst rocky desertification in complex and heterogeneous karst environments. The main conclusions are as follows:

1. Vegetation indices are designed based on the unique spectral features of green vegetation can be directly used to estimate the PV fraction. Comparison the performance of extraction of PV fraction, narrow band vegetation indices are better than broad band vegetation indices. However, the vegetation indices cannot be directly used to extract the symbols of karst rocky desertification for the evaluation indicators including multiple land surface types.

2. As thin, little amount and not continuous, the bare soil has little effect on the inversion of PV fraction with remote sensing, especially for hyperspectral remote sensing. NPV, exposed carbonate rocks, and bare limestone soils have distinguishing spectral features in SWIR (2000—2400 nm).

3. The new designed KRDSI can be effectively used to estimate the faction of NPV, soil and rock. However, because of the different types and the weathering processes of carbonate rocks, the accuracy of extraction of rate of bedrock is relatively low. Further study is needed to analyze the spectral variability of different types and weathering extent of carbonate rocks.

4. With the development of remote sensing, especially the hyperspectral technique, it holds the potential to using imaging spectroscopy (e.g. EO-1 Hyperion) to directly extract evaluation indicators of karst rocky desertification combined with vegetation indices and KRDSI.

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石漠化遥感评价因子提取研究

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1 前言

中国西南喀斯特地区位于世界三大连片喀斯特发育区之一的东亚片区中心, 面积约54万km², 由于CO2-H2O-CaCO3系统活跃的生物过程和化学过程, 形成受特殊地质背景制约的脆弱生态系统, 属于全球变化敏感区, 在区域碳循环中发挥着独特作用(袁道先, 1999; 刘丛强 等, 2009)。西南喀斯特区地处亚热带季风性湿润气候区, 地表复杂度高, 地物交错分布且土被不连续, 具有高度的时空异质性; 土壤保水能力低, 植被以石生旱生为主, 片段化严重, 与同纬度的其它地区相比差异明显, 加之近现代人类不合理的土地利用, 导致植被遭受破坏, 土壤侵蚀严重, 基岩大面积裸露, 产生了以石漠化为特征的生态环境退化(鞠建华 等, 2006; 王世杰和李阳兵, 2007)。

遥感技术具有宏观、快捷、经济、信息综合等优势, 是快速、大面积石漠化定性评价、信息定量提取必不可少的手段(鞠建华 等, 2006)。石漠化遥感监测研究通常的做法是先确定石漠化评价或分类的指标体系, 确定各个指标阈值, 建立石漠化分级指标; 然后通过遥感图像的波段组合增强显示, 确定石漠化遥感影像特征, 建立遥感解译标志; 最后再以人工目视解译为主, 辅以人机交互解译确定石漠化程度和区域(熊康宁 等, 2002; 吴虹 等, 2002; 李阳兵 等, 2006)。这种方法解释工作量大, 解译速度慢, 解译者需要对石漠化的遥感影像表现有深刻地认识, 特别是对不同程度的石漠化, 用人眼目视判断在量化上存在较大困难。如果是由不同解译者来对同一区域进行解译, 结果可能会出
现很大的差异，影响石漠化信息提取的效率和准确性，同时降低了不同地区石漠化信息提取结果的可比性(岳跃民，2010)。

关于石漠化的评价指标，目前仍没有统一的方案(Wang等，2004；王世杰和李阳兵，2005；鞠建华等，2006)，因此，遥感监测中石漠化需要考虑遥感技术的特点并结合石漠化监测、评价专业的应用需求去研究。遥感主要是用来提供石漠化评价指标的定量、可靠监测方法。从石漠化的表现看，石漠化是类似荒漠化的特殊景观，岩石裸露度及其植被覆盖度是石漠化主要的地面表现特征，也是评价石漠化的关键指标；同时，石漠化又是一种动态土地退化过程，是植被、基岩、土被等多种地表覆盖要素的综合反映，由于植被的物候特征，已落叶植被及其凋落物等干枯的失去光合作用能力的植被覆盖、土壤覆盖等对表征石漠化信息也有重要作用。因此，评价石漠化时需要同时考虑多种地物类型覆盖。对于植被信息的提取，基于绿色植被的特有光谱特征而发展的植被指数能够有效地表达植被的生长状况。然而，目前还没有一个光谱指数能够直接指示石漠化是否发展及发展程度信息。因此，急需发展地物混杂条件下面向石漠化信息提取的石漠化遥感评价因子提取方法。

本研究设计了不同石漠化程度下光谱测量试验，测量不同喀斯特地表要素覆盖下的复合地物类型光谱，探讨现有主要地表覆盖信息遥感提取方法提取石漠化遥感评价因子的有效性，研究喀斯特石漠化表征信息的光谱特征差异，发展可以直接估算石漠化评价指标的光谱指数模型，并基于Hyperion高光谱成像数据进行初步实证，为石漠化信息准确快速遥感提取提供方法和理论基础。

2 研究方法

2.1 光谱测量方法

基于地面实测高光谱数据来模拟不同石漠化退化程度的光谱响应特征，暂时不考虑地形地貌、阴影和太阳高度角等对光谱的影响。试验区域为中国科学院环江喀斯特生态系统观测研究站，该站为目前中国西南喀斯特地区唯一的国家野外生态系统观测研究站，多年平均气温16.5℃—20.5℃，平均降水量为1389.1 mm。区内自然植被以喜钙、耐旱、耐贫瘠的灌木和草丛群落为主。光谱测量时间为2008年12月8日—13日。针对绿色植被PV(photosynthetic vegetation)、干枯植被NPV(non-photosynthetic vegetation)、裸露石灰土Soil)、裸露碳酸盐岩Rock)等4种典型地物的不同覆盖度区域进行测量，共得到有效样本91个。其中，由于试验条件限制，测量的植被主要为草丛和低矮的灌木，不包含高大树木。

光谱测量采用美国ASD(Analytical spectral device)公司的ASD Field SpecPro FR光谱仪，视场角25°，光谱反射率经过标准参考板校正，光谱范围为350—2500 nm，采样间隔在350—1000 nm范围内为1.4 nm，在1000—2500 nm范围内为2 nm。测量时天气状况良好，基本无云无风，时间为10:00—14:00。野外地面实测光谱时关键是要控制ASD光谱仪的探头高度及其视场，具体方法如图1所示，光谱仪视场角为25°，探头高度为1.5 m，这样视场范围为半径为0.33 m的圆。并测量视场范围内每地物类型的光谱作为混合光谱分析的端元。测量光谱的同时在与探头相同位置的设置一台数码相机垂直拍摄光谱仪视场范围。利用Adobe Photoshop剪取视场范围大小，确定视场内的主要地物类型，对视场内的典型地物类型基于ENVI遥感图像处理软件进行K-Means非监督分类，再利用IDL计算视场内主要典型地物类型覆盖度信息。

![图1 光谱测量方法](image)

2.2 地物光谱特征选择与提取

地面实测光谱数据大量的光谱波段为了解地物提供了及其丰富的波谱信息，然而波段的增多也必然导致信息的冗余和数据处理复杂性的增加。为此，光谱特征空间的减少和优化显得十分重要。
光谱特征空间减少的方式可以概括为两种：特征选择和特征提取(童庆禧等,2006)。通过光谱特征选择，可以强化那些最具可分性的光谱波段。而经过特征提取后的光谱特征空间中，其新的光谱向量应该是反映特定地物某一性状的一个光谱参量，或者是有别于其他地物的光谱参量。本研究采用Asner和Lobell提出的一种光谱特征提取方法——“约束光谱”(tied spectra)来分析石漠化典型地物的光谱特征，即给定特征波段范围，每一波段的反射率都减去作为约束点(tie point)波段的反射率，从而增强不同地物类型的光谱吸收特征差异并区分不同地物类型(Asner和Lobell,2000;Lobell和Asner,2001)。

式中，ρ是一个光谱波段的反射率，ρc是样本在短波红外波段的波长对应的混合光谱反射率，a、b和c分别是光谱吸收特征的两吸收肩和吸收谷处的波长，ρ0是两点(a,ρa)和(b,ρb)直线连线与波长c对应的光谱反射率值(图2)。
波长a、b和c具体位置的确定是根据干枯植被、碳酸盐岩或石灰土在短波红外波段的光谱吸收特征的先验知识，其值并不唯一，是代表光谱吸收特征的吸收双肩和吸收谷的波长。此外，混合光谱与复合覆盖度的相关系数也证明这些波长在短波红外波段与干枯植被、碳酸盐岩和石灰土的覆盖度具有高相关系数(图3)，这些具有较高相关系数的波长理论上能够提供更多的关于干枯植被、碳酸盐岩和石灰土等非绿色植被的覆盖度信息。光谱指数系数a、b、c的波长位置参见(Yue等，2010)。

### 3.2 石漠化表征信息光谱特征差异原因分析

绿色植物由于叶绿素的强烈吸收造成可见光波段区间的低反射和叶内组织造成的近红外波段高反射和高透射，导致植被光谱特征与其他地物类型有强烈差异。对于碳酸钙、石灰土和干枯植被等非绿色植被地物覆盖来说，在短波红外波段(SWIR，2000—2400 nm)附近范围光谱特征差异显著。为了便于对比分析，图4是经过等间距补偿的“约束光谱”变换增强后的碳酸盐岩、石灰土和干枯植被的反射率光谱，其光谱特征差异主要是由以下原因造成的：

- 蒙脱石晶格结构振动单吸收
- 粘土矿物双吸收
- 碳酸钙根离子吸收
- 有机碳化合物双吸收

对于干枯植被来说，在2100 nm和2300 nm附近形成两个比较明显的吸收特征，这主要是由于纤维素、木质素等干物质中有机化合物中的C-H和O-H基团等的振动造成的(Curran，1989)。石灰土在中心波长为2200 nm形成一个明显的单吸收特征，这主要是由
于水吸收和粘土中的蒙脱石晶格振动共作用形成的(Ben-Dor 等, 1999; Chabrilat 等, 2004); 同时, 在2330 nm附近形成CO₂较明显的吸收峰值。而对碳酸盐岩来说, 由于富含粘土矿物使其在2200 nm附近形成双吸收特征, 另外在2350 nm附近形成明显的CO₂吸收特征(傅碧宏, 1996; Chabrilat 等, 2004)。

3.3 宽/窄植被指数提取石漠化信息的有效性

根据上述选择的植被指数, 分别计算了植被指数与绿色植被覆盖度(PV)的回归方程(表1、表2)。由表可知,无论是宽波段植被指数还是窄波段植被指数与绿色植被覆盖度均有着较好的线性关系,测定系数(r²)均较高。这主要是由于植被指数都是基于植被特有的光谱响应特征构建的:绿叶中的叶绿素在0.5—0.7 μm的可见光波段有两个强吸收谷,反射率一般小于20%;但在0.7—1.3 μm的近红外波段,由于叶肉海绵组织结构中有许多空腔,具有很大的反射表面,反射率较高。这些植被指数与绿色植被的高相关性,表明可以利用植被指数来估算绿色植被覆盖度, 尤其是基于三离散波段的植被指数, 光谱遥感连续的光谱特征能够描述植被叶绿素的吸收特征, 而宽波段反射率不能有效地描述叶绿素的吸收特征。

表1 高光谱植被指数与绿色植被覆盖度回归分析

<table>
<thead>
<tr>
<th>植被指数</th>
<th>线性回归</th>
<th>r²</th>
</tr>
</thead>
<tbody>
<tr>
<td>RVI</td>
<td>y=12.52x-14.88</td>
<td>0.79</td>
</tr>
<tr>
<td>NDVI</td>
<td>y=1.28x-0.32</td>
<td>0.78</td>
</tr>
<tr>
<td>SAVI</td>
<td>y=1.84x-0.18</td>
<td>0.79</td>
</tr>
<tr>
<td>MSAVI</td>
<td>y=1.79x-0.13</td>
<td>0.79</td>
</tr>
<tr>
<td>TVI</td>
<td>y=0.05x-0.04</td>
<td>0.82</td>
</tr>
<tr>
<td>MCARI</td>
<td>y=7.32x-0.00</td>
<td>0.81</td>
</tr>
</tbody>
</table>

表2 宽波段植被指数与绿色植被覆盖度回归分析

<table>
<thead>
<tr>
<th>植被指数</th>
<th>线性回归</th>
<th>r²</th>
</tr>
</thead>
<tbody>
<tr>
<td>RVIₓ</td>
<td>y=0.15x-0.18</td>
<td>0.79</td>
</tr>
<tr>
<td>RVIᵧ</td>
<td>y=0.15x-0.19</td>
<td>0.78</td>
</tr>
<tr>
<td>NDVIₓ</td>
<td>y=1.31x-0.30</td>
<td>0.78</td>
</tr>
<tr>
<td>NDVIᵧ</td>
<td>y=1.35x-0.34</td>
<td>0.77</td>
</tr>
<tr>
<td>SAVIₓ</td>
<td>y=1.96x-0.23</td>
<td>0.78</td>
</tr>
<tr>
<td>SAVIᵧ</td>
<td>y=1.99x-0.27</td>
<td>0.77</td>
</tr>
<tr>
<td>MSAVIₓ</td>
<td>y=1.91x-0.18</td>
<td>0.78</td>
</tr>
<tr>
<td>MSAVIᵧ</td>
<td>y=1.92x-0.21</td>
<td>0.78</td>
</tr>
<tr>
<td>TVIₓ</td>
<td>y=0.05x-0.13</td>
<td>0.81</td>
</tr>
<tr>
<td>TVIᵧ</td>
<td>y=0.05x-0.15</td>
<td>0.80</td>
</tr>
<tr>
<td>MCARIₓ</td>
<td>y=0.43x+0.07</td>
<td>0.69</td>
</tr>
<tr>
<td>MCARIᵧ</td>
<td>y=0.42x+0.06</td>
<td>0.69</td>
</tr>
</tbody>
</table>

从不同类型的植被指数表现来看, 三角植被指数TVI在各类型植被指数中表现最优, 是探测喀斯特绿色植被的最佳植被指数; 而应用最为广泛的NDVI表现一般, 这主要是由于当植被覆盖度大于60%时, NDVI将容易达到饱和, 对绿色植被覆盖度变化不敏感(Gitelson 等, 2002)。宽波段的SAVI和MSAVI表现略好于RVI和NDVI, 但改进效果不明显(表2); 对于宽波段的SAVI和MSAVI来说(表1), 没有改进对绿色植被覆盖信息的提取, 因此考虑土壤背景影响的植被指数(SAVI、MSAVI)表现与RVI、DNVI基本相当, 说明利用遥感技术特别是高光谱遥感技术来提取喀斯特地区绿色植被覆盖度时, 土壤背景对绿色植被覆盖度信息的提取影响很小, 这可能主要是由于喀斯特地区土被分布浅薄、较少且不连续造成的。

3.4 线性光谱分解提取石漠化信息的有效性

线性光谱分解能够比较成功地提取绿色植被的覆盖度信息, 裸土的覆盖信息提取效果不理想, 测定系数r²为0.54, 而对于干枯植被和裸露基岩, 都不能有效提取(图5(a) (b) (c))。这可能是由以下原因造成的: 我们是基于实测混合像元内部的主要地物类型的平均光谱作为端元光谱, 而实际上不同地物类型的光谱差异比较大, 特别是不同碳酸盐岩类型光谱特征差异(傅碧宏, 1996), 另外, 碳酸盐岩的侵蚀也导致其光谱变化(Younis 等, 1997); 同时,由于大尺度的光谱混合完全可以被认为是一种线性混合(Nash和Conel, 1974), 而小尺度的内部物质混合是非线性的(Singer, 1981), 由于非线性多次散射, 加上阴影的影响, 导致线性光谱分解提取石漠化信息结果不理想。这说明基于混合光谱分析能够比较容易地提取喀斯特地区绿色植被的覆盖信息,
而对于干枯植被、裸土、裸露基岩等非绿色植被的覆盖信息很难直接有效提取。

3.5 石漠化综合指数模型验证

表3列出了干枯植被、碳酸盐岩、和石灰土的覆盖度与KRDSI的回归方程。由表可知，对于NPV，用来描述纤维素和木质素等干物质中有机碳化合物的吸收深度的KRDSI-NPV和覆盖度也有着较好的线性相关性，$r^2$达到0.70。NPV覆盖度越高，其干物质吸收特征越可能在混合光谱上表露出来，则其吸收特征变量数值也可能越大，因而在喀斯特研究地区，可以考虑利用这些纤维素吸收特征参数建立估算NPV覆盖度的模型。

表3 干枯植被、碳酸盐岩和石灰土覆盖度与KRDSI的回归分析

<table>
<thead>
<tr>
<th>光谱指数</th>
<th>线性回归</th>
<th>$r^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>NPV</td>
<td>KRDSI3-NPV</td>
<td>$y=23.73x+0.21$</td>
</tr>
<tr>
<td>Soil</td>
<td>KRDSI3-soil</td>
<td>$y=38.74x+0.22$</td>
</tr>
<tr>
<td>Rock</td>
<td>KRDSI3-rock</td>
<td>$y=18.24x+0.08$</td>
</tr>
</tbody>
</table>

喀斯特地区广泛分布的石灰土因具有较高的粘土含量而表现出粘土矿物特有的吸收特征，同理也可以尝试利用吸收特征的强弱来判断土壤覆盖度的高低。描述这种吸收深度的KRDSI-soil和土壤覆盖度有着较好的线性相关性，测定系数最高达0.73。

岩石裸岩率的高低是描述喀斯特地区石漠化程度的最重要的指标之一，由于喀斯特地区地表破碎，地物分布复杂，目前为止还没有有效的裸岩率计算方法。碳酸盐岩是喀斯特发育的物质基础，根据其矿物、化学成分含量的差异可分为石灰岩和白云岩。白云岩的CO$_2$基团吸收特征的中心波长位于2300 nm附近，而石灰岩的CO$_2$基团吸收特征的中心波长位于2340 nm附近，随着碳酸盐岩中白云石含量的增加，其中心波长位置向短波方向移动(傅碧宏, 1996)。吸收特征的偏移和变化导致了利用吸收特征参数估算裸岩率的困难，加上碳酸盐岩不同侵蚀程度对光谱特征的影响(Younis等, 1997)，导致这些光谱指数与裸岩率的线性相关性比较低，KRDSI3-rock测定系数为0.55。

3.6 线性光谱分解与KRDSI指数模型对比分析

为了说明构建的石漠化综合指数KRDSI的优越性，将其提取石漠化表征信息的有效性与线性光谱分解的提取结果进行了对比分析(图5)。对NPV来说，石漠化综合指数KRDSI提取的NPV覆盖度值与实际测量值线性回归的测定系数$r^2$为0.70，而线性光谱分解(LSU)的$r^2$为0.30。对碳酸盐岩和石灰土来说，石漠化综合指数KRDSI的精度也比线性光谱分解高。说明石漠化综合指数KRDSI，能够用来比较有效地直接提取干枯植被、裸露碳酸盐岩和石灰土的覆盖度信息。但石漠化综合指数KRDSI，提取裸露碳酸盐岩的效果不是很理想，这可能主要是因为不同碳酸盐岩类型(石灰岩和白云岩)及不同碳酸盐岩侵蚀程度造成碳酸盐岩的光谱吸收特征变化，而本研究在构建石漠化综合指数KRDSI时暂时没考虑这些因素对裸露碳酸盐岩吸收光谱特征的影响。

![图5 石漠化综合指数KRDSI与线性光谱分解(LSU)提取石漠化表征信息的有效性的对比 (Yue等, 2010)](image-url)
3.7 石漠化遥感评价因子提取

由上述分析可知，利用高光谱成像数据基于植被指数和KRDSI可以直接有效提取石漠化遥感评价因子。本研究利用Hyperion高光谱成像数据(获取时间为2008-03-03)，结合NDVI植被指数和KRDSI，对石漠化典型区域(广西大化县七百弄乡附近)的绿色植被覆盖、干枯植被覆盖、土被覆盖和基岩裸露率等石漠化遥感评价因子进行提取。由于喀斯特地区的高度景观异质性，混合像元效应严重，因此，采用实测地面调查验证点的方法对遥感评价因子提取结果进行初步实证，共获取有效地面验证点21个，验证结果见表4。可以看出，基于植被指数和KRDSI能够比较有效地直接提取石漠化遥感评价因子。

表4 实测地物覆盖信息与Hyperion提取结果的线性回归

<table>
<thead>
<tr>
<th>覆盖类型</th>
<th>基岩裸露率</th>
<th>土被覆盖</th>
<th>干枯植被覆盖</th>
<th>绿色植被覆盖</th>
</tr>
</thead>
<tbody>
<tr>
<td>r^2</td>
<td>0.9058</td>
<td>0.6828</td>
<td>0.7173</td>
<td>0.5295</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.0470</td>
<td>0.0593</td>
<td>0.0390</td>
<td>0.1059</td>
</tr>
</tbody>
</table>

4 结 论

中国西南喀斯特地区以石漠化为特征的生态环境退化严重，与西北地区沙漠化和黄土地区水土流失并列为中国3大区域生态问题之一。随着国家对喀斯特石漠化区生态环境问题的日益重视，特别是《岩溶地区石漠化综合治理规划大纲(2006—2015)》的实施，更快更准确获取石漠化信息突显重要，这为遥感技术在该领域的应用提出了新的要求和挑战。本研究基于地面光谱试验和Hyperion高光谱成像数据，发展了地物混杂条件下面向石漠化信息提取的石漠化遥感评价因子的提取方法。主要研究结论如下：

(1) 植被指数是根据绿色植被的特有光谱特征而发展的，可以用来直接有效提取绿色植被覆盖信息。高光谱植被指数相对于宽波段植被指数提取绿色植被覆盖精度高；石漠化评价指标包括多种地物覆盖类型，很难基于植被指数来直接有效提取表征石漠化信息的非绿色植被覆盖。

(2) 由于喀斯特地区土壤分布浅薄，较少且不连续，利用遥感技术特别高光谱遥感技术来提取喀斯特地区绿色植被覆盖度时，可以暂时不考虑土壤背景的影响；裸露碳酸盐岩、石灰土、干枯植被等石漠化非绿色植被覆盖信息在短波红外波段(SWIR，2000—2400 nm)光谱特征差异显著。

(3) 基于的喀斯特石漠化综合指数KRDSI能够比较有效地提取裸露碳酸盐岩、石灰土和干枯植被等非绿色植被的覆盖信息，但由于不同碳酸盐岩类型(石灰岩和白云岩)及不同碳酸盐岩侵蚀程度造成碳酸盐岩的光谱吸收特征变化，导致基岩裸露率的提取精度较低。未来需要进一步研究碳酸盐岩属性及侵蚀程度等导致的光谱特征差异，完善石漠化综合指数模型。

(4) 随着遥感技术特别是高光谱遥感技术的发展，利用高光谱成像数据(如EO-1 Hyperion)，结合植被指数和石漠化综合指数KRDSI可以来直接提取喀斯特石漠化遥感评价因子。

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