Study on the Monitoring of Karst Plateau Vegetation with UAV Aerial Photographs and Remote Sensing Images

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Abstract. Southwest China is considered to be one of the three major karst regions in the world. Fractional vegetation cover (FVC) can be an important factor in delineating the various steps in the karst regional evolutionary process that is expected to results in rocky desertification. Remote sensing using unmanned aerial vehicles (UAVs) is a new method of investigating, extracting, and monitoring vegetation. In this method, error correction of the results of five other classification methods that involve imaging using visible-light bands (EXcess Green, Normalized Green-Red Difference Index, Normalized Green-Blue Difference Index, Red-Green Ratio Index and Visible-band Difference Vegetation Index), it was found that the classification accuracy for non-vegetation areas is improved after combining the normalized difference vegetation indices of the remote sensing images.

1. Introduction
Land degradation is the most destructive erosion process in southwest China [1], where karst is the main natural landscape; the ecosystem in this region is extremely vulnerable. Southwest China is considered to be one of the three major karst regions in the world [2]. In this region, there is an abundance of precipitation and hydrological processes, resulting in serious geological hazard to the terrestrial ecosystem; the phenomenon that has been occurring in this region is called the karst rocky desertification (KRD), and it has drawn widespread attention [3]. As a consequence, the possibility of sustainable development of agricultural practices is extremely limited. KRD can cannot be reversed; however, it can be monitored by monitoring the fractional vegetation cover (FVC). The FVC can also be used to delineate the various steps in the KRD evolution process [4].

The FVC is the percentage value of the vegetation per unit area; it can be used to measure the growth or abundance of terrestrial vegetation. Accurate determination of the vegetation coverage and the laws governing its variations are globally of great significance to revealing the ecological quality of...
ecosystems, particularly under the current trend of rapid global environmental changes. Current methods for calculating FVC most commonly involve a field vegetation survey or remote sensing image interpretation. The former has significant spatial and temporal heterogeneity, making its application to regional-scale FVC trend evaluation difficult. Remote sensing technology, on the other hand, uniquely allows for assessing FVC trends on a regional scale. Therefore, it has been employed as an effective and quick data resource in many studies on vegetation cover. In recent years, there has been rapid development of the UAV technology, and using it to gather remote sensing images on vegetation has become an important method of obtaining information on vegetation. UAV remote sensing technology has great environmental adaptability, low cost, high efficiency, and high time efficiency, making it the most recent widely used method of investigating, extracting, and monitoring vegetation.

This study extracted vegetation information from aerial photographs captured by UAVs and free remote sensing images captured in the visible-light band. The Weining Plateau in the karst region of Southwest China was taken as the research area. The aim was to establish an effective vegetation monitoring method using remote sensing that can be applied: to vegetation identification research using aerial photographs of any destination, to rapidly extract vegetation information, to derive a method that can expand the application scope of UAV remote sensing, and to promote the quantitative application of UAV remote sensing.

2. Overview of the Research Area

![Figure 1. Schematic diagram of the research area](image)

The study area is in the Zhuopu Demonstration Ranch of the Weining Plateau Grassland Experiment Station in Guizhou Province. (Weining County, Guizhou Province; geographical location: 104°07'25"E, 27°12'30"N; altitude: 2442 m; annual average temperature: 8.7°C) [5]. The aerial photographs in Figure 1 were collected on April 19, 2018, using the Phantom 4 drone from Dji, from an aerial height of 500 m. The sky was blue and cloudless at the time of capturing the images. To avoid distortion of the edges...
during aerial photo montage, a 1 km x 1 km area at the center of photographs was selected for the study (shown in the yellow box in Fig. 1). The yellow triangles are points added after human visual interpretation of the images. Three bands of red, green, and blue were used and the spatial resolution is greater than 0.2 m.

3. Research Methods

3.1. Method involving the vegetation index and traditional UAV photographs captured using visible light

The vegetation index is typically calculated using remote sensing images captured in both the visible-light and near-infrared bands; examples are the normalized difference vegetation index (NDVI) and the enhanced vegetation index (EVI). Vegetation indices calculated using images captured in only the visible light band are few; main examples are excess green (EXG), normalized green-red difference index (NGRDI), normalized green-blue difference index (NGBDI) which is modeled on NGRDI, red-green ratio index (RGRI), and visible-band difference vegetation index (VDVI) fabricated by imitating the construction principle and form of NDVI [5]. The calculation formulas are as follows: (1)

\[ EXG = 2 \times \rho_{green} - \rho_{red} - \rho_{blue} \]  

\[ NGRDI = \frac{\rho_{green} - \rho_{red}}{\rho_{green} + \rho_{red}} \]  

\[ NGRDI = \frac{\rho_{green} - \rho_{blue}}{\rho_{green} + \rho_{blue}} \]  

\[ RGRI = \frac{\rho_{red}}{\rho_{green}} \]  

\[ VDVI = \frac{2 \times \rho_{green} - (\rho_{red} + \rho_{blue})}{2 \times \rho_{green} + (\rho_{red} + \rho_{blue})} = \frac{2 \times \rho_{green} - \rho_{red} - \rho_{blue}}{2 \times \rho_{green} + \rho_{red} + \rho_{blue}} \]
Where $\rho_{\text{red}}$, $\rho_{\text{green}}$, and $\rho_{\text{blue}}$ represent the reflectivity or pixel values of the red, green and blue bands respectively.

After calculating a vegetation index, the next step is to set an appropriate threshold. Pixels with vegetation index is greater than the threshold value are classified as vegetation and those with values less than the threshold as categorized as non-vegetation [6]. In this study, the NDVI information extraction process from remote sensing images also used the threshold.

3.2. Extraction of vegetation information from UAV aerial photographs and remote sensing images

Extracting vegetation information from images captured using only the visible-light band is easy; however, this method of extraction causes the misidentification of certain objects, such as a water body, as shown in Figs. 3E and 3F. Therefore, this study used UAV photographs captured in the visible light band to develop its proposed method combining UAV aerial photographs and remote sensing images. The aerial photographs from this study can be conveniently and quickly applied to obtain vegetation information in the local area. The specific work flow of the proposed method is shown in Fig. 2.

Figure 2. Flow chart of the vegetation information extraction method using a combination of UAV aerial photographs and remote sensing images

First, NDVI and VDVI were calculated for the remote sensing images and aerial photographs, and the respective vegetation index layers were delineated. Then the 100 sample points shown in Fig. 1 were visually interpreted using the aerial photographs to obtain a layer of these training sample points. Part of the data on this layer provided vegetation and non-vegetation pixel information for vegetation information extraction. The remaining data validated the accuracy of the result layers after classification. The classification rule for the result layers is shown in Fig. 2. This classification step can maintain the classification accuracy corresponding to the NDVI while maximally retaining the accuracy of interpretation of the UAV aerial photographs.
This is because: 1) when the results of interpretation of the remote sensing image and aerial photograph are consistent, the classification type is clear. That is, when the pixel categorization using NDVI for the remote sensing image and VDVI threshold for the aerial photograph are both vegetation or non-vegetation, the pixel category is unambiguous. 2) If the results for remote sensing image and aerial photograph are inconsistent, which may be due to a discrepancy in the resolutions of the images, the advantages of using both types of images will need to be integrated to accurately extract vegetation information. For instance, when the result for the remote sensing image is non-vegetation while that for the aerial photograph is vegetation, the difference could be caused by errors such as the incorrect demarcation of the boundaries of ponds; in such cases, the pixel is classed as non-vegetation. 3) When the result for the remote sensing image is vegetation while that for the aerial photograph is non-vegetation, which may be ascribed to the coarse resolution of the remote sensing image causing a poor distinction among the boundaries of non-vegetation areas, the pixel is also classed as non-vegetation.

4. Results and Discussions

4.1. Spatial distribution information according to five vegetation indices in the UAV aerial photographs captured with visible-light bands

![Spatial distribution information on aerial photographs](image)

Figure 3. Spatial distribution information on aerial photographs (A, true color synthesis of the three bands; B, red band; C, green band; D, blue band; E, EXG algorithm; F, NGRDI algorithm; G, NGBDI algorithm; H, RGRI algorithm; I, VDVI algorithm)

According to existing research [5], the numerical ranges of vegetation and non-vegetation pixels do not overlap in the red and blue bands. Only bare soil overlaps with vegetation in the green band, so it is
hard to distinguish vegetation from some non-vegetation using only the green and red bands or using vegetation index structured only in the green and blue bands, as shown in Figs. 3A-3D. The results for the five vegetation indices calculated in the visible light bands are shown in Figs. 3E-3I. The brighter the hue is, the larger the value is, and the better the vegetation growth is. The result in Fig. 3F is too dark, while that in Fig. 3H is too bright.

4.2. Classification Results of Five Vegetation Indexes of UAV and NDVI of Remote Sensing Images

Table 1. Statistical eigenvalues of EXG, NGRDI, NGBDI, RGRI, VDVI, and NDVI

| Statistical eigenvalues of each index | EXG | NGRDI | NGBDI | RGRI | VDVI | NDVI |
|--------------------------------------|-----|-------|-------|------|------|------|
| Vegetation                           |     |       |       |      |      |      |
| mean                                 | 22.1| 0.0469| 0.0379| 0.9136| 0.0421| 0.5640|
| sd                                   | 15.2| 0.0430| 0.0270| 0.0769| 0.0304| 0.1005|
| se                                   | 2.0 | 0.0054| 0.0034| 0.0098| 0.0039| 0.0128|
| n                                    | 62  | 62    | 62    | 62   | 62   | 62   |
| Non-vegetation                       |     |       |       |      |      |      |
| mean                                 | -2.9| -0.0005| -0.0102| 1.0013| -0.0055| 0.4018|
| sd                                   | 11.2| 0.0371| 0.0282| 0.0649| 0.0191| 0.1193|
| se                                   | 1.8 | 0.0060| 0.0046| 0.0105| 0.0031| 0.0194|
| n                                    | 38  | 38    | 38    | 38   | 38   | 38   |

Theoretically, the range of EXG is [-255, 255], that of NGRDI, NGBDI, and VDVI is [-1, 1], that of RGRI is [0, +∞] ([0, 11] in this study) and that of NDVI is [0, 1]. To distinguish between vegetation and non-vegetation features, statistical analysis was performed using the 100 sample points uniformly distributed in Fig. 1, as shown in Table 1.

In this example, the thresholds of the bimodal histogram threshold method and histogram entropy threshold method were not evident. Hence, this study utilized statistical indicators to directly determine the thresholds. After subtracting the standard error from the vegetation average of each vegetation index, plus its non-vegetation average and standard error, the average value of the two was obtained. The final calculation showed put the vegetation information extraction thresholds of the six vegetation indices at 9.5, 0.0240, 0.0144, 0.9578, 0.0179, and 0.4862.

Figure 4. Vegetation information extraction results for (A) EXG, (B) NGRDI, (C) NGBDI, (D) RGRI, (E) VDVI and (F) NDVI (Green indicates vegetation cover; Pink indicates non-vegetation areas)
The vegetation distribution results corresponding to each vegetation index obtained by extracting vegetation information using the above thresholds are shown in Fig. 4.

4.3. Analysis of the results of vegetation information extraction from UAV aerial photographs in combination with remote sensing images

In the results shown in Fig. 4, with the exception of the relatively poor RGRI results in Fig. 4D and the coarser resolution of the NDVI results in Fig. 4F, the results (in Fig. 4A, 4B, 4C, and 4E) using various vegetation indices to extract vegetation information are generally consistent, with differences only in the details. In addition, compared with the extraction results for NDVI, the results for the other indices present different degrees of misidentification of ponds and houses. By employing the classification method shown in Fig. 2 and combining it with remote sensing images to extract vegetation information from UAV aerial photographs, this study improves the accuracy of classification. The extraction results using the proposed method are shown in Fig. 5. Compared with Fig. 4, the areas for both ponds and houses are corrected in Fig. 5.

Figure 5 Spatial distribution map of the vegetation information extracted for (A) EXG, (B) NGRDI, (C) NGBDI, (D) RGRI, and (E) VDVI from UAV aerial photographs in combination with remote sensing images

4.4. Verification of the proposed method

As shown in Table 2, after correcting for the five indices, it was found that the classification accuracy of non-vegetation areas was significantly improved when NDVIs in the remote sensing images were combined; the classification of ponds and houses was more accurate than before. However, forest and farmland areas with low greenery were still not accurately demarcated.
Table 2. Accuracy evaluation of the vegetation information extraction methods for EXG, NGRDI, NGBDI, RGRI, and VDVI from UAV aerial photographs in combination with remote sensing images

| Classification method using UAV aerial photographs combined with remote sensing images | Classification methods using the vegetation indices for images captured with visible light only |
|---|---|
| Vegetation area categorization accuracy (%) | Vegetation area categorization accuracy (%) |
| Non-vegetation area categorization accuracy (%) | Non-vegetation area categorization accuracy (%) |
| EXG | 71.0 | 94.7 | 75.8 | 92.1 |
| NGRDI | 59.7 | 97.4 | 62.9 | 94.7 |
| NGBDI | 72.6 | 94.7 | 88.7 | 89.5 |
| RGRI | 16.1 | 81.6 | 33.9 | 5.3 |
| VDVI | 69.4 | 94.7 | 72.6 | 92.1 |

5. Conclusion
Taking the Weining Plateau in the southwestern karst area of China, where severe rocky desertification prevails, as the research area, this study proposed and verified a new method to optimize vegetation information extraction using five indices from UAV aerial photographs captured in the visible-light band, adopting NDVI classification results of remote sensing images. Compared with the classification method used before optimization, this method shows a significant improvement in the classification of non-vegetation areas, especially in the case of ponds and houses. However, this method also introduces certain errors, such as misidentification of forest and farmland areas with low greenery.

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