

Gobi Vegetation Recognition Based on Low-Altitude Photogrammetry Images of UAV

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Abstract. Vegetation distribution information is crucial to the environmental protection of Gobi. The traditional method to obtain vegetation distribution information is building vegetation index which can be used as the threshold for vegetation recognition, with the spectral characteristics of vegetation in remote sensing images from satellite or aviation, especially the near infrared band. In recent years, low-altitude photogrammetry technology based on UAV has developed rapidly. But the UAV images do not contain near-infrared band information, many researchers have adopted visible light spectral characteristics to construct new vegetation index and achieved many progress. In this paper, taking the Gobi region of northwest China as a example, we introduced the methods for multi-scale segmentation and classification of DOM which generated from the UAV images. Further, based on eCognition Developer, we extracted visible light-based vegetation indices including NGRDI, NGBDI, VDVI, GLI, and ExG, and assessed the vegetation recognition effect of these five indices.

1. Introduction

The traditional vegetation recognition mainly uses the reflection difference between vegetation and other ground objects in the near infrared band and red band, to build vegetation indices such as NDVI (Normalized Difference Vegetation Index, NDVI), RVI (Ratio Vegetation Index, RVI) and DVI (Difference Vegetation Index, DVI). These vegetation indices can be used as criteria for distinguishing vegetation from other ground objects [1]. The images which containing near infrared band are acquired by satellite or aerial remote sensing, and have inherent problems such as long acquisition cycle, vulnerability to clouds, and high costs. In recent years, with the miniaturization and intellectualization of UAV, low-altitude photogrammetry technology has made considerable progress and widely applied to the fields such as mapping and renewal of large-scale topographic maps, geological environment survey [2], electric power engineering [3, 4], marine resources monitoring [5], wind energy survey and development [6], transportation [7] etc. However, the images based on low-altitude photogrammetry of UAV only have the visible light band. Without the near infrared band, vegetation indices like NDVI cannot be constructed. Many researchers have done a lot of attempts to building new vegetation index based on visible light band and achieved many progress. As early as 1995, Woebbecke et al. [8] tested four vegetation indices based on the visible light band, including R-G, G-R, (G-B)/[R-G], and ExG (Excess Green Index, ExG), found that ExG has high accuracy in distinguishing vegetation and soil. Learning from the building principle of NDVI, Wang Xiaoqin et al. [9] had built VDVI (Visible-Band Difference Vegetation Index, VDVI), and found that the recognition accuracy of VDVI reached over 90%, which indicating that the index is applicable to the healthy green



vegetation recognition from the UAV images. Ding Leilong et al. [10] used four vegetation indices, including NGRDI (Normalized Green-Red Difference Index, NGRDI), ExG, ExG-ExR (Excess Green Minus Excess Red Index, ExG-ExR) and GLI (Green Leaf Index, GLI), to process the UAV images, and found that the indices can quickly and accurately identify the vegetation coverage area, and the accuracy reached over 90%. In this paper, taking the Gobi region of Northwest China as the experimental area, we had generated the large-scale DOM (Digital Orthophoto Map, DOM) by the low-altitude photogrammetry technology of UAV. On this basis, the multi-scale segmentation of the DOM was performed by eCognition Developer [11], a powerful development environment for object-based image analysis. The vegetation indices such as NGRDI, NGBDI, VDV, GLI, and ExG were used to recognize vegetation, and the accuracy of these indices were compared and analyzed.

2. Experimental area, Images and Research Methods

2.1. Overview of the experimental area

The experimental area is located in Heshuo County, Xinjiang Uygur Autonomous Region, and is the edge of the alluvial fan at the southern foot of Tianshan Mountains. Its average altitude is 1,400 meters, and the climate is temperate continental with hot summer and cold winter. Throughout the year, the area is dry and dominated by drought-tolerant plants such as camel thorn, haloxylon ammodendron. In summer, rainwater often gathers into temporary small lakes in low-lying areas. As rainfall decreases and sunshine evaporates, the lakes dry up and form saline lands.

2.2. Images

According to the "Specifications for aerophotogrammetric field work of 1:500 1:1000 1:2000 topographic maps" [12], the original images were captured by Dapeng CW-10 drone [13], which equipped with a Nikon D810 digital camera, at a planned route of about 560 meters high. The resolution of each image is 7360 pixels \times 4912 pixels. According to the "Specifications for office operation of low-altitude digital aerophotogrammetry" [14], combined with the camera lens distortion coefficient and the control point coordinate information, the DOM was generated by the Pix4D [15], a professional drone mapping and photogrammetry software. As shown in Fig 1, the DOM size of experimental area is 14304 pixels \times 12204 pixels. The main features in the DOM are vegetation, dunes, saline lands and road.



Figure 1. Digital Orthophoto Map of the experimental area.

2.3. Research methods

Segmentation and classification are two steps of vegetation recognition. First, the DOM is segmented by the segmentation algorithm and converted into image objects. Then, the image objects are classified according to the vegetation index. The technology roadmap is shown in Fig 2.

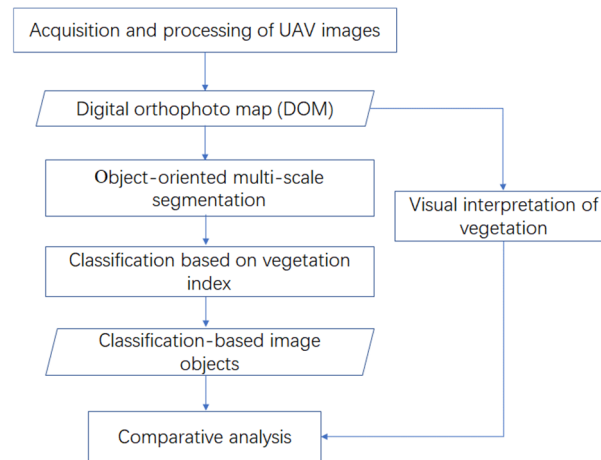


Figure 2. Technology Roadmap.

2.3.1 Object-oriented multi-scale segmentation technology

There are many segmentation algorithms including histogram threshold segmentation, feature space cluster segmentation, region segmentation, edge detection segmentation, and object-oriented multi-scale segmentation. Among them, object-oriented multi-scale segmentation is commonly used in high-resolution images due to better segmentation results [16]. According to the spectral features and the spatial features such as geometric shapes and textures in the image, the object-oriented multi-scale segmentation technique sets the parameters and generates the polygons, which can describe ground objects well. The multi-scale segmentation algorithm in eCognition Developer focuses on three kinds of parameters such as scale parameter, color parameter and shape parameter. The shape parameter contains smoothness and compactness. The scale parameter defines the maximum standard deviation of the weighted image layer of the image object under the homogeneity criterion. The size of the image object formed by the segmentation increases as the increasing of scale parameter. The relationship between color parameter and shape parameter is [color parameter]=1-[shape parameter]. The relationship between smoothness and compactness is [smoothness]=1-[compactness]. The homogeneity of the image objects is determined by the interaction of these parameters. The effect of automatic interpretation by eCognition Developer depends on the merits of the established rule set.

2.3.2. Classification Techniques Based on Vegetation Index

Different objects in the image have different reflection and absorption, for example, the healthy green vegetation has strong reflection in green band and near infrared band, and absorption in blue band and red band. The mathematical formula is built based on the reflection and absorption to minimize the non-vegetation information while enhancing the vegetation information [17].

The NGRDI (Normalized Green-Red Difference Index, NGRDI) is a normalized ratio of the difference between green band and red band, aiming to eliminate the influence of different irradiance on the spectral characteristics of the vegetation [18]. The formula is as follows:

$$NGRDI = (G - R) / (G + R) \quad (1)$$

The NGBDI (Normalized Green-Blue Difference Index, NGBDI) is a normalized ratio of the difference between green band and blue band [19]. The formula is as follows:

$$NGBDI = (G - B) / (G + B) \quad (2)$$

The VDVI (Visible light band Difference Vegetation Index VDVI) was built by Wang Xiaoqin et al. [9] referencing to the principle and form of NDVI. The formula is as follows:

$$VDVI = \frac{2G - (B + R)}{2G + (B + R)} = \frac{2G - B - R}{2G + B + R} \quad (3)$$

The GLI was first proposed by Louhaichi et al. to record the effect of grazing on wheat [20]. The formula is as follows:

$$GLI = (2G - R - B) / (2G + R + B) \quad (4)$$

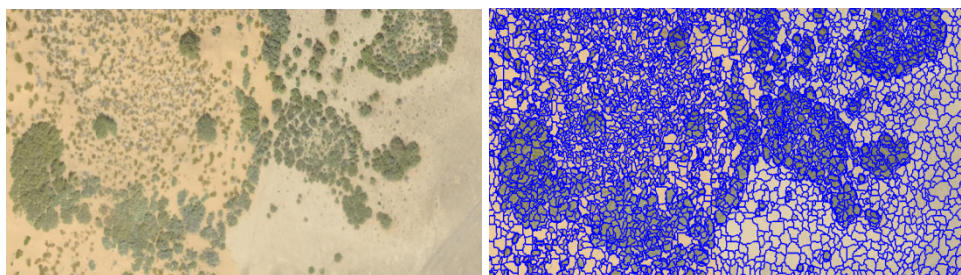
The ExG is often used to identify crops and soil [8]. The formula is as follows:

$$\begin{aligned} ExG &= 2g - r - b \\ r &= (R / R_{\max}) / (R / R_{\max} + G / G_{\max} + B / B_{\max}) \\ g &= (G / G_{\max}) / (R / R_{\max} + G / G_{\max} + B / B_{\max}) \\ b &= (B / B_{\max}) / (R / R_{\max} + G / G_{\max} + B / B_{\max}) \end{aligned} \quad (5)$$

In the above formula, B, G, and R are the values of blue band, green band and red band of the pixel or image object, respectively. B_{\max} , G_{\max} , and R_{\max} are respectively the maximum values of the B, G, and R components, and their values are 255 in the 24 bit storage mode.

3. Verification Experiment

In eCognition Developer, the DOM of the experimental area is segmented by multi-scale segmentation. Since the visible light band of the image object is used to build the vegetation indices after segmentation, the red, green and blue bands are included in the segmentation process and the weights of the bands are all set with 1. Considering the uneven distribution of vegetation, for example, the vegetation on the border of saline land is lush, but on the dune is scattered, the segmentation parameters need to be scientifically set, neither miss the characteristics of small features nor overly fragment and consume a lot of program running time. After many experiments, the scale parameter 20, the shape factor 0.5, and the compactness factor 0.6 are selected. The segmentation effect of the local area which in experimental area is shown in Fig 3.



(a) Partial DOM in experimental area

(b) Multi-scale segmentation effect

Figure 3. Multi-scale segmentation effect of local area which in experimental area.

As can be seen from Fig 3(b), there are clear boundaries between vegetation, dunes and saline lands; and small individual plants can also have obvious boundaries with dunes, indicating that segmentation works well and lays the foundation for classification.

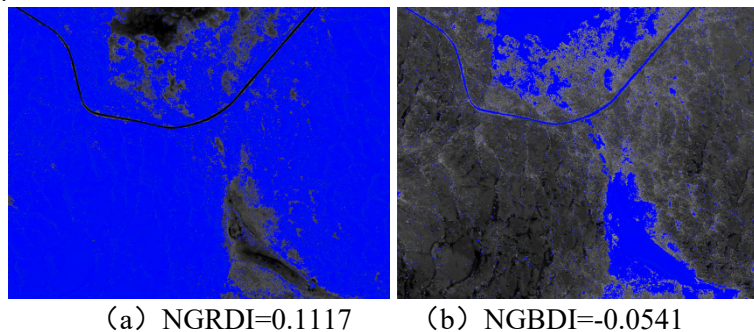
The NGRDI, NGBDI, VDVI, GLI, and ExG were constructed on the image object layer which generated by multi-scale segmentation. 50 objects corresponding to vegetation, dunes, saline lands, and road were selected. The mean, standard deviation, and numerical range of the five vegetation indices were calculated and shown in Table 1.

Table 1. Statistical characteristics of NGRDI, NGBDI, VDVI, GLI, and ExG

Vegetation Indices (VI)	Ground Objects	Mean	Standard deviation	Range	
NGRDI	Vegetation	0.1689	0.0572	0.1117	0.2261

NGBDI	Saline lands	0.0924	0.0154	0.0771	0.1078
	Road	0.0644	0.0145	0.0499	0.0788
	Dunes	0.1390	0.0122	0.1268	0.1512
	Vegetation	-0.0440	0.0101	-0.0542	-0.0339
	Saline lands	-0.0472	0.0083	-0.0555	-0.0389
	Road	-0.0295	0.0125	-0.0420	-0.0170
	Dunes	-0.0757	0.0056	-0.0814	-0.0701
	Vegetation	0.0525	0.0121	0.0404	0.0645
	Saline lands	0.0186	0.0031	0.0155	0.0216
VDVI	Road	0.0150	0.0014	0.0136	0.0163
	Dunes	0.0179	0.0041	0.0138	0.0220
	Vegetation	0.0497	0.0219	0.0278	0.0717
	Saline lands	0.0179	0.0031	0.0148	0.0210
GLI	Road	0.0164	0.0022	0.0142	0.0185
	Dunes	0.0196	0.0023	0.0173	0.0218
	Vegetation	-0.1563	0.0471	-0.2034	-0.1092
	Saline lands	-0.4397	0.0557	-0.4954	-0.3840
ExG	Road	-0.4247	0.0202	-0.4449	-0.4045
	Dunes	-0.4528	0.0479	-0.5007	-0.4049

It can be seen from Table 1, the NGRDI range of the vegetation has no intersection with saline lands and road, but intersects with dunes, indicating that NGRDI cannot extract vegetation from dunes; the NGBDI range of vegetation does not intersect with road and dunes, while overlaps with saline lands, indicating that NGBDI cannot extract vegetation from saline lands. The VDVI, GLI, and ExG ranges of the vegetation did not intersect with saline lands, road, and dunes, indicating that the above three vegetation indices can extract vegetation from the other three types of ground objects. From the corresponding standard deviations of the VDVI, GLI, and ExG indices, we can see that the standard deviation of VDVI is the smallest, indicating that its classification stability is the best among these three indices. But the ExG difference between the minimum of vegetation and the maximum of saline lands was 0.1806, indicating that the ExG can also effectively identify vegetation. The GLI difference between the minimum of vegetation and the maximum dune is 0.0060, indicating that although the GLI algorithm is stable, it is easy to incorrectly identify the dunes as vegetation. Using the 'update range' function in eCognition Developer to gradually adjust the threshold of the 5 indices, the results are shown in Fig 4.



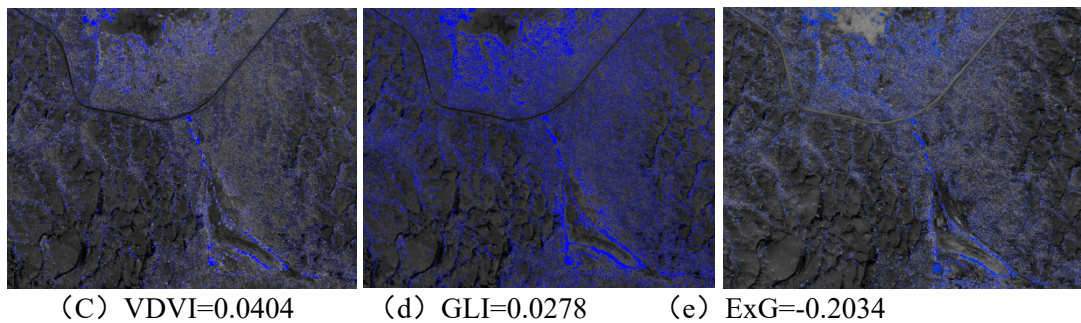


Figure 4. Classification effects based on NGRDI, NGBDI, VDVI, GLI and ExG thresholds.

It can be seen from Fig 4, under the NGRDI algorithm, vegetation and dunes are seriously confused; under the NGBDI algorithm, vegetation is seriously confused with road and saline lands. These two algorithms have poor recognition of vegetation. The VDVI, GLI and ExG algorithms can distinguish vegetation from road, dunes and saline lands. Classification results are in accordance with the statistical results in Table 1.

The classified images, including images of VDVI, GLI, and ExG, and DOM of the experimental area were synchronous displayed by using View Classification and Pixel View functions of eCognition Developer. Through visual interpretation, select 200 vegetation objects on DOM to test the accuracy of eCognition Developer automatic classification. The results are shown in Table 2.

Table 2. Evaluation of vegetation recognition accuracy of VDVI, GLI, and ExG

Vegetation Indices (VI)	Number of correct classification	The number of misclassified	Accuracy
VDVI	187	13	93.5%
GLI	181	19	90.5%
ExG	182	18	91%

As can be seen from Table 2, the accuracy of the three indices is over 90%, indicating that the three indices can be used for the recognition of Gobi vegetation.

4. Conclusion

Based on low-altitude photogrammetry images of UAV, the recognition effects of NGRDI, NGBDI, VDVI, GLI and ExG indices of Gobi vegetation were evaluated and verified. We found that NGRDI, NGBDI cannot be used for the recognition of Gobi vegetation. According to the research of Ding L L et al. [10], the accuracy of NGRDI in identifying winter wheat reached 90%, shows that the same vegetation index for different vegetation types, may has different recognition effects. The VDVI, GLI, and ExG can effectively distinguish vegetation from other ground objects and achieve the accuracy of over 90%, indicating that these indices can be used for Gobi vegetation recognition based on low-altitude photogrammetry images of UAV.

In the follow-up studies, attention should be paid to the seasonal variation of the vegetation index. In particular, the spectral characteristics of the winter vegetation may become confused with the dunes. At the same time, although the texture factor was introduced in the multi-scale segmentation process, only the visible light band was used in the process of vegetation recognition. The texture feature was not fully used. The research on the vegetation texture feature needs to be strengthened to enable effective recognition of vegetation in a more complex environment.

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