



Article

Automatic Identification of Shrub-Encroached Grassland in the Mongolian Plateau Based on UAS Remote Sensing

Yu Dong ^{1,2,3} , Huimin Yan ^{1,*}, Na Wang ^{1,2} , Mei Huang ¹ and Yunfeng Hu ¹¹ Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China² University of Chinese Academy of Sciences, Beijing 100049, China³ Department of Natural Resources of Jilin Province, Changchun 130000, China

* Correspondence: yanhm@igsnr.ac.cn; Tel.: +86-10-64889467

Received: 30 March 2019; Accepted: 5 July 2019; Published: 9 July 2019



Abstract: Recently, the increasing shrub-encroached grassland in the Mongolian Plateau partly indicates grassland quality decline and degradation. Accurate shrub identification and regional difference analysis in shrub-encroached grassland are significant for ecological degradation research. Object-oriented filter (OOF) and digital surface model (DSM)-digital terrain model (DTM) analyses were combined to establish a high-accuracy automatic shrub identification algorithm (CODA), which made full use of remote sensing products by unmanned aircraft systems (UASs). The results show that: (1) The overall accuracy of CODA in the Grain for Green test area is 89.96%, which is higher than that of OOF (84.52%) and DSM-DTM (78.44%), mainly due to the effective elimination of interference factors (such as shrub-like highland, well-grown grassland in terrain-depression area, etc.) by CODA. (2) The accuracy (87.5%) of CODA in the typical steppe test area is lower than that (92.5%) in the desert steppe test area, which may be related to the higher community structure complexity of typical steppe. Besides, the shrub density is smaller, and the regional difference is more massive in the typical steppe test area. (3) The ground sampling distance for best CODA accuracy in the Grain for Green test area is about 15 cm, while it is below 3 cm in the typical and desert steppe test area.

Keywords: object-oriented filter; digital orthophoto map; digital surface model; excess green minus excess red (ExG-ExR); Hough circles

1. Introduction

In recent years, the shrub-encroachment phenomenon in natural and artificial grassland in the Mongolian Plateau has been continuously emerging, which indicates to some extent the grassland quality decline and the occurrence of grassland degradation [1,2]. In addition, the grassland ecosystems of the Mongolian Plateau have undergone unprecedented changes in the past hundred years under the dual effects of climate change and human activities [3,4]. Especially, overgrazing has weakened the ecological dominance of herbaceous vegetation such as *Leymus Chinensis* and *Artemisia*, which has resulted in a continuous expansion of shrubs such as *Caragana* [5,6]. This kind of constant development of shrubs has not only changed the original natural community structure but also altered the ecosystem functionality. Furthermore, the production of animal husbandry and livelihoods of herdsman have been affected or reformed where the shrub-encroachment is more severe [7–9]. Therefore, identifying shrubs and analyzing the biological mechanism of shrub-encroachment is of great significance for the sustainable development of grassland in the Mongolian Plateau.

In most studies of shrubs in grassland, the traditional method is to use portable Global Positioning System (GPS) devices, spectrometers, or other equipment to conduct field investigations on the

shrubs. After that, indoor analysis and statistics with samples were usually carried out [10]. There are advantages of field investigations for studying shrubs in particularity, flexibility, and exactitude, but it is time-consuming and arduous in fieldwork. Therefore, this approach is often only applicable to local farms or a big area with scattered grassland sample points in practical research [11,12]. To achieve long-term and rapid monitoring of large continuous areas of shrub-encroached grassland, satellite remote sensing data has been used by many scholars to analyze spectral characteristics and changes in grassland where shrubs exist [13]. However, due to the small size of shrubs, spectral characteristics of them are often submerged in mixed pixels [14,15]. Even with high-resolution remote sensing satellite data, the recognition ability of shrubs in the early growth stage is congenitally inadequate.

Compared with satellite remote sensing, unmanned aerial vehicle remote sensing (UAV-RS) has advantages of higher resolution, more flexibility, and is less susceptible to disturbances of cloud, fog, etc. [16]. With the rapid development of computer vision technology and automated flight control technology, UAV-RS plays an increasingly important role in ecology research [17]. Many scholars have tried to use automatic or semi-automatic methods to monitor the vegetation of cultivated land and woodland ecosystems. For example, tree type detection and plant density estimation of wheat crops were conducted by UAV-RS, and the results have satisfactory accuracy [18,19]. Nonetheless, grassland analysis was tried with UAV by scholars recently, and this kind of application has become a frontier of UAV-RS research [20,21].

The goal of this study was to develop an automatic shrub identification approach with UAV-RS technology in shrub-encroached grassland in the Mongolian Plateau. Therefore, this approach provides technical support for the real-time, fast, automated grassland degradation monitoring in the Mongolian Plateau. Section 2 is a review of related works on shrub identification study and UAV-RS study. Section 3 introduces the primary materials of this study. Section 4 describes the shrub identification approach (CODA) conducted in this study in detail. Section 5 contains results with CODA on the Grain for Green, the typical steppe and desert steppe test area. Sections 6 and 7 are the discussion of the findings and central conclusions.

2. Background

With the development of the UAV industry, unmanned aircraft systems (UASs) have penetrated and affected a variety of ecological research fields [22–24]. Small UAS (S-UAS), with small-size and easy-to-use characteristics, plays an essential role in passive optical remote sensing [25]. Many scholars have tried to retrieve grassland structure, biomass, and other information based on UAS, which can be summarized as the following two kinds of research methods. One type of technique that some scholars use is optical vegetation indexes (OVIs) or spectral characteristic analysis to quantitatively study grassland ecosystem [26], in which OVIs have a profound characterization ability for grassland growth [20,27]. Among many OVIs, the ExG-ExR has been proven to have good results in vegetation extraction [28], which is applied in many types of research [29,30]. Another method that some scholars use is image classification, decision tree analysis and other approaches to analyze grassland types qualitatively [21], in which object-oriented classification technology has a high accuracy of optical remote sensing in grassland [31]. However, these methods depend on the reflectivity of several electromagnetic bands and are often analyzed with only three optical image bands (red, green, and blue). Facing the complex structures of grassland ecosystems [32,33], the methods as mentioned above always confuse shrubs with well-growing grass-patches.

Besides the digital orthophoto map (DOM), the digital surface model (DSM) is one other of the critical products of UAS remote sensing [34], where shrubs can always be represented as “bulges” in the DSM. This feature of shrubs brings a new research approach for shrub recognition [35]. Formerly, the DSM has been used to study vegetation identification and classification by scholars [36,37], but these applications mainly depend on LiDAR point-cloud products and mainly attribute to the high accuracy of LiDAR products [38,39]. With the development of UAS, many vegetation analyses based on DSM products by UAS emerges [24,40]. There are many conductive approaches for forest, cropland, and grassland

ecosystem developed with DSM by UAS [19,41,42]. For UAS remote sensing, DSM does have some difficulty in the automated processing of steep edges such as buildings and trees: either the UAS is required to collect a large number of UAS images at multiple angles, or manual editing at a later stage is expected, which will undoubtedly considerably increase the time consumption and manpower [43,44]. Fortunately, shrubs are often scattered or clustered [45]. Besides, unlike buildings and trees with a huge DSM drop in edges, DSM changes relatively smoothly in the shrub area, which is easy to be adequately monitored by UAV. Therefore, DSM is feasible for the extraction of grassland shrubs.

In this study, a high-precision automatic algorithm for grassland shrub identification was developed by the combining object-oriented filter and DSM-DTM algorithm (CODA). CODA was designed for using the information of DOM and DSM products of UAS remote sensing as fully as possible. The algorithm was implemented to shrub identification of typical steppe and desert steppe in the Mongolian Plateau and the scale effect of UAS grassland remote sensing was further analyzed by information entropy theory. As a result, the research in this paper will provide technical support for deepening and expanding the research on the mechanism of shrub-encroached grassland and grassland degradation.

3. Materials

3.1. The Experimental Sites

Shrub-encroached grasslands mainly occur in arid or semi-arid areas. In this study, a sample typical steppe area and a sample desert steppe area were selected as the research sites. In addition, the researchers also selected an experimental area of Grain for Green grassland for the development and validation of CODA. Therefore, the experimental sites of shrub-identification in this paper were the Grass for Green Test Area (GGA), the Typical Steppe Test Area (TSA) and the Desert Steppe Test Area (DSA), as shown in Figure 1. The GGA ($110^{\circ}48'23.40''\text{E}$ $41^{\circ}27'11.02''\text{N}$ in the World Geodetic System (WGS) 1984 coordinate system) is located in the farming-pastoral ecotone about 40 km southeast of Darhan Muminggan Joint Banner in Baotou City, Inner Mongolia Autonomous Region, China. Shrub density in the GGA is extremely high, which facilitated the development and verification of CODA: along spacing of planted shrubs was just about 3–5 m, and across spacing was less than 1 m. The TSA ($116^{\circ}07'16.58''\text{E}$ $43^{\circ}38'49.38''\text{N}$ in the WGS 1984 coordinate system) is located in a typical steppe area, 35 km south of Xilingol League, Inner Mongolia Autonomous Region, China. The main grass species in the TSA is *Leymus Chinensis*, and the grassland thrives. The DSA ($112^{\circ}31'20.06''\text{E}$ $42^{\circ}36'7.09''\text{N}$ in the WGS 1984 coordinate system) is located in the desert steppe area, 20 km southwest of Sonid Right Banner of Xilingol League, Inner Mongolia Autonomous Region, China. Due to the scarcity of precipitation in the DSA, the grassland coverage is relatively low.

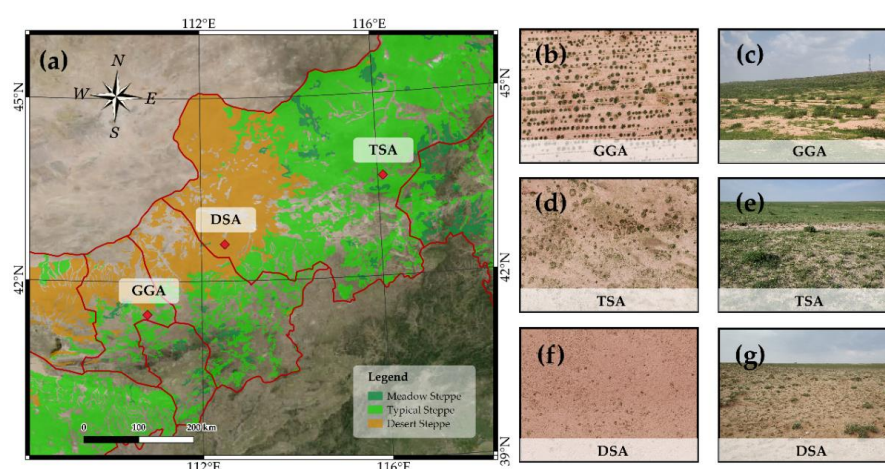


Figure 1. Experimental areas: (a) locations of the Grass for Green Test Area (GGA), the Typical Steppe Test Area (TSA) and the Desert Steppe Test Area (DSA); (b,c) unmanned aircraft system (UAS) image and photo of the GGA; (d,e) UAS image and photo of the TSA; (f,g) UAS image and photo of the DSA.

3.2. The Acquisition of UAS Images

The Mavic Pro S-UAS (developed by DJI Technology Co., Ltd., Shenzhen, China) was used to collect UAS images in the GGA, TSA, and DSA. The essential information of UAS images is shown in Table 1. The Mavic Pro was equipped with a 1/2.3 inch complementary metal oxide semiconductor (CMOS) camera (also known as FC220) with a maximum aperture of $f/2.2$ and a field of view (FOV) of 78.8° . To ensure image quality and reflectivity accuracy, the aperture size was fixed to $f/2.0$, the shutter time was set to 0.1 s, and the ISO was set to 1600. Given the lack of normalization correction in each band of the subsequent processing, to ensure the homogeneity of imageries, all the photos were taken in the morning from 8 to 10 o'clock (there was merely cloud cover in study area at this time also). Additionally, the image was saved in RAW format with 4000×3000 resolution, which stored photos with floating data type. Furthermore, the photo overlay referred to the specification standard for aerial photography in China, which requires an along overlap of no less than 60% and an across overlap of no less than 30% [46].

Table 1. Basic information of remote sensing acquisition of UAS images.

Sites	Date of Flight	Photo Count	AGL ¹ (m)	Overlap (along/across)	GSD ² (cm)	Point Cloud Density (points·m ⁻²)
GGA	31 July 2018	179	100	80%/40%	3.00	1215.66 (± 56.21)
TSA	28 July 2018	167	100	80%/40%	3.00	1059.14 (± 159.73)
DSA	30 July 2018	221	120	80%/60%	3.30	1017.32 (± 121.52)

¹ AGL refers to above ground level; ² GSD refers to ground sampling distance; ³ values in brackets represent standard deviations.

After photo acquisition, DOMs and DSMs were composed by Pix4d Mapping software with the same sampling distance. Additionally, no ground control points (GCPs) were used, but the GPS and global navigation satellite system (GLONASS) on the Mavic Pro provided enough information for aerial triangulation. The imageries were saved as GeoTiff format with WGS 1984 universal transverse Mercator (UTM) projected coordinate system (Zone: 49N, EPSG: 32649). As a result, the generated DOMs and DSMs had high accuracy: the number of point clouds matching was not less than 20,000 key points per photo, averaging 27,421 key points per photo. The average point cloud densities in the three sites varied from 1017.32 to 1215.66 points per square meter, which contained enough topography information to generate the DSMs. For further accuracy assessment of DSMs and DOMs, at least three points were selected in each image and their location information was obtained by GPS devices.

4. Methods

The aim of this research was to automatically identify and count shrubs in shrub-encroached grassland based on the combined object-oriented filter (OOF) and DSM-DTM algorithm (CODA), which was divided into three main processes: (1) Object-oriented filter: The DOM was objectified by multiresolution segmentation algorithm, and the average value of ExG-ExR of each object was calculated as a feature. Hence, the shrubs were extracted by using this feature and threshold classification. (2) DSM-DTM filter: The DTM was retrieved automatically from DSM mainly by a DTM filter (slope based) tool and interpolation tool in System for Automated Geoscientific Analyses (SAGA) firstly, and then the difference between DTM and DSM was obtained. Thus, the shrub area was obtained by open operation optimizing and μ filtering finally. (3) Combination and counting: overlay analysis was used to combine the results of OOF and DSM-DTM. Then, the number of identified shrubs was counted by the Hough circles method. The flow chart of shrub identification based on CODA is shown in Figure 2.

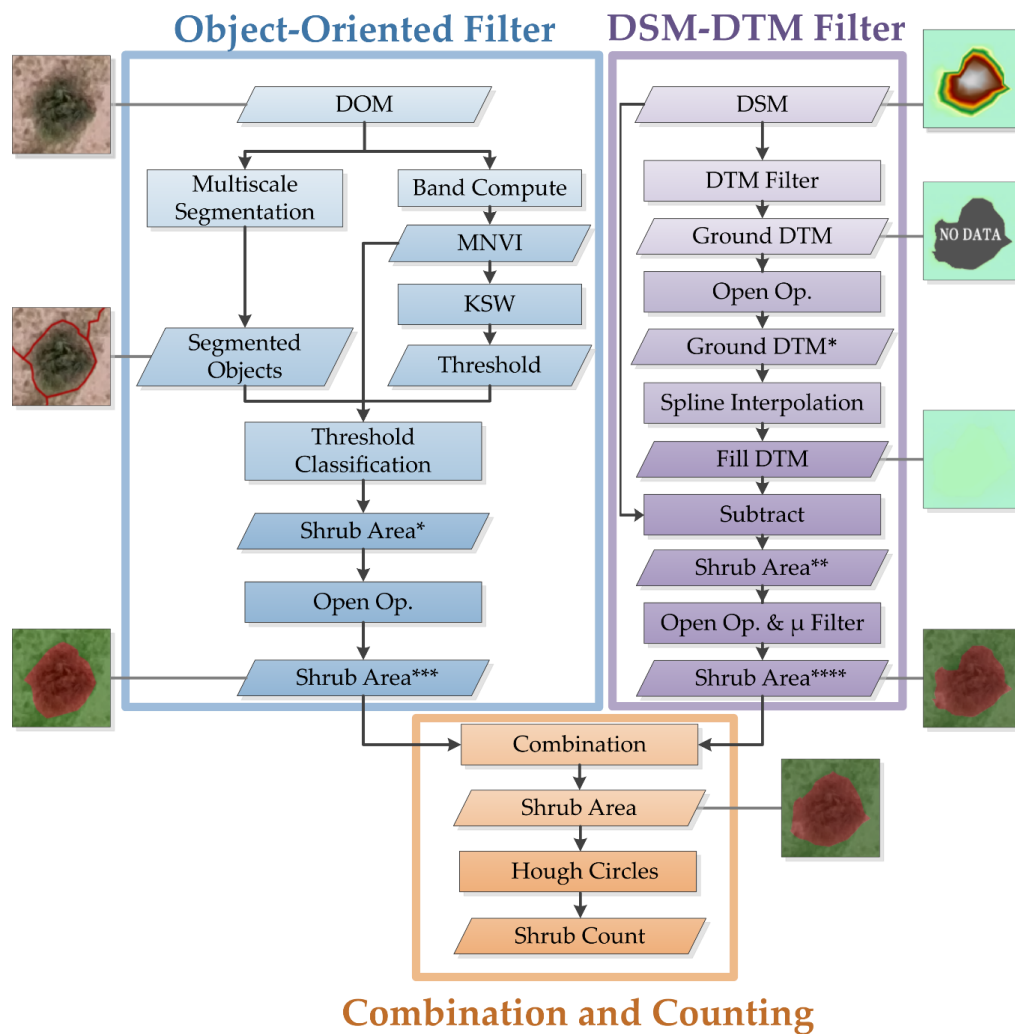


Figure 2. Flow chart of the combining object-oriented filter and digital surface model (DSM) - digital terrain model (DTM) algorithm (CODA) for shrub identification (where Open Op. refers to open operation).

4.1. Object-Oriented Filter (OOF)

There are three main parts in OOF: multiresolution segmentation, ExG-ExR threshold classification, and open operation optimization, which will be introduced in the following sections.

4.1.1. Multiresolution Segmentation

The multiresolution segmentation algorithm mainly relies on eCognition Developer software, which divides one grassland image into several objects, with internal mean features, for classification by the spectral and shape characteristics of the ground objects in the optical bands. Multiresolution segmentation is a kind of top-down segmentation algorithm, which mainly utilizes spatial heterogeneity differences and segmentation scale settings to limit the size of merged regions. After many attempts, when the scale was set to 150, the segmentation effect is the most efficient and accurate.

$$\text{Heterogeneity} = \varepsilon_1 x + (1 - \varepsilon_1) y \quad (1)$$

where x indicates the spectral heterogeneity, ε_1 is the weight of spectral heterogeneity, and y is the shape heterogeneity. The calculation formula of y is as follows:

$$y = \varepsilon_2 u + (1 - \varepsilon_2) v \quad (2)$$

where u indicates the tightness of one object region, ε_2 is the weight of tightness, and v indicates the smoothness of the region boundary of an object. After many attempts, when $\varepsilon_1 = 0.6$ and $\varepsilon_2 = 0.5$, the results of multiresolution segmentation can effectively separate shrubs from grassland. Since the shrubs have apparent features in shape and spectrum, as well as in smoothness and tightness, these parameter settings can adequately consider the above factors.

4.1.2. Threshold Classification Based on ExG-ExR Features

In this threshold classification, ExG-ExR index was used to extract shrub objects. Compared with grasslands with lower coverage, shrubs have more prominent spectral characteristics, specifically in the ExG-ExR indicator, which is a vegetation index based on red, green, and blue bands [18]. The calculation formula of ExG-ExR is as follows:

$$\text{ExG} - \text{ExR} = \text{EGVI} - \text{ERVI} \quad (3)$$

where EGVI represents Excess Green Vegetation Index, and ERVI represents Excess Red Vegetation Index. The formulas of EGVI and ERVI are as follows:

$$\text{EGVI} = 2G - R - B \quad (4)$$

$$\text{ERVI} = 1.4R - B \quad (5)$$

where R, G, and B represent the relative reflectivity of red, green, and blue respectively. In this study, the average of ExG-ExR is computed for each segmented object as its one feature (ExG-ExR_{avg}).

The higher the ExG-ExR_{avg} is, the better the vegetation grows. Thus, the objects with higher ExG-ExR_{avg} are more likely to be shrubs. On the contrary, the lower the ExG-ExR_{avg} is, the lower the grassland coverage is. Consequently, the objects with lower ExG-ExR_{avg} are more likely to be grassland (Figure 3b). The ExG-ExR threshold for shrub identification can be determined by supervised or unsupervised methods. Specifically, supervised methods can achieve high segmentation accuracy, but it is time-consuming and laborious, which is not conducive to the automatic analysis and application of CODA in different regions and for different UAS remote sensing images.

Among the unsupervised methods, the threshold selection in maximum entropy segmentation is based on the criterion that the statistical characteristics of random variables are most in line with the actual situation. When the sum of the information entropy of the two segmentation parts is the maximum, the threshold can divide the images into two sections as target and background, which is called the maximum information principle. This principle is widely used in image binarization, machine learning, and other fields. Accordingly, the best histogram entropy method (KSW) is adopted as the image segmentation method in this study [47], ensuring the geographical suitability of this method and to promote its migration.

KSW information entropy is generally defined as:

$$H = - \int_{-\infty}^{+\infty} p(x) \log[p(x)] dx \quad (6)$$

where $p(x)$ refers to the probability of the occurrence of the numerical value x . This paper assumed that T is the image segmentation threshold of $\text{ExG} - \text{ExR}_{avg}$: when $x > T$, the set of the corresponding x with lower image value was denoted as B; conversely, the set of the corresponding x with higher image value was denoted as O. At this time, the probability (P_B) of x appearing in set B and the probability (P_O) of x appearing in set O are calculated as follows:

$$P_O = \int_{-\infty}^T p(x) dx \quad (7)$$

$$P_B = \int_T^{+\infty} p(x)dx \quad (8)$$

The formulas for calculating information entropy H_B and H_O are as follows:

$$H_O = \int_{-\infty}^T \frac{p(x)}{P_O} \cdot \ln \left[\frac{p(x)}{P_O} \right] dx \quad (9)$$

$$H_B = \int_T^{+\infty} \frac{p(x)}{P_B} \cdot \ln \left[\frac{p(x)}{P_B} \right] dx \quad (10)$$

When $H_O + H_B$ is maximum, the corresponding T is regarded as the final threshold of $\text{ExG} - \text{ExR}_{avg}$ segmentation. In this paper, T was used for threshold classification. When $\text{ExG} - \text{ExR}_{avg} > T$, the object was classified as a shrub area. Conversely, the object was classified as grassland, as shown in Figure 3c.

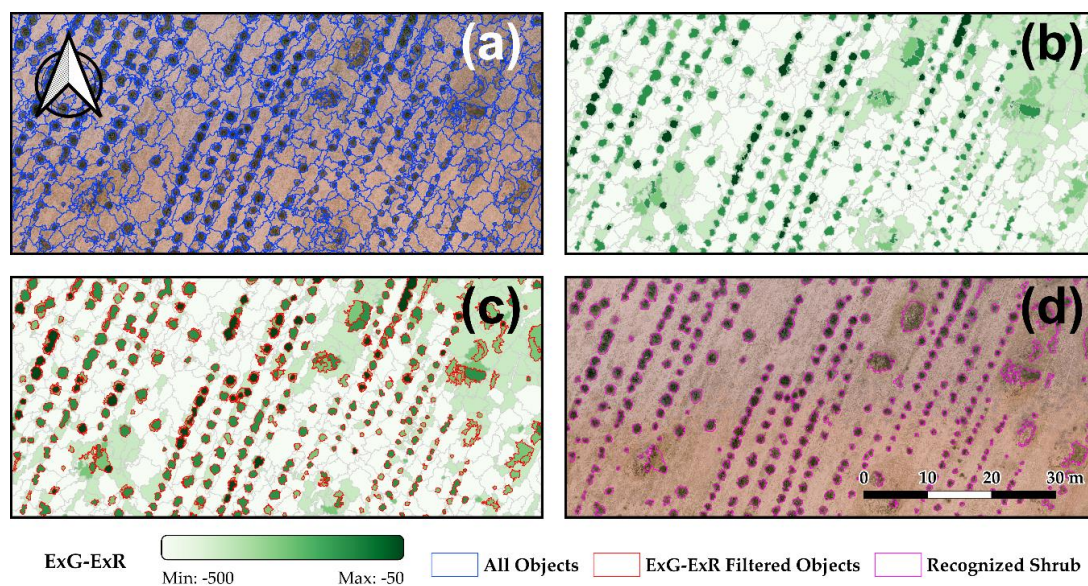


Figure 3. Object-oriented filter (OOF) based shrub identification approach: (a) multiresolution segmentation result; (b) ExG-ExR features of objects; (c) threshold classification result; (d) identified Shrub Area.

4.1.3. Open Operation Optimizing

To recognize the shape of shrubs more accurately, the scale of multiresolution segmentation algorithm was set relatively large, which would make some generated objects very small, or even only a few pixel sizes, that is, the phenomenon of “salt and pepper”. To remove these interference factors, the open operation method in morphology was used to optimize the results: the image was corroded firstly and then expanded to remove “salt and pepper”, while the identified positions and shapes of potential shrub areas remain unchanged. The result of shrub identification after opening operation is shown in Figure 3d.

4.2. DSM-DTM Filter

The OOF could extract most of the shrubs, but there were still cases of omissions and commissions in the experiment. This was mainly because some non-shrub areas often have similar characteristics to the shrubs (higher ExG-ExR). However, these areas can often be excluded by topographic analysis. For example, low depressions with well-grown grass are different from raised shrubs in DSM but are often confused in DOM.

Because the grassland in the study area may have a particular slope in bare land, it is impossible to extract the shrubs directly by threshold classification. Therefore, this study used the method of producing DTM to shield the influence of topographic factors. This method is from now on referred to

as the DSM-DTM. There are three main parts in the DSM-DTM filter: DTM extraction, shrub extraction, and optimization.

In this study, the DTM filter (slope based) tool in SAGA GIS was used to separate DSM into two parts: bare earth and removed objects. After many attempts in the extraction process, the segmentation was the best when the search radius parameter was set to 2, and the slope parameter was set to 0.5. Thus, the bare earth part was used as the surface DTM. However, the effect of the above extraction process was limited, because the phenomenon of “salt and pepper” often occurred. The parts with low accuracy were removed by the open operation method again. As a result, the surface DTM after the open operation in a sample area is shown in Figure 4b. On this basis, the whole region DTM was estimated by interpolating surface DTM with the B-spline interpolation method, as shown in Figure 4c. Therefore, the difference between DTM and DSM was the potential shrub area (PSA), of which the formula is as follows:

$$PSA = DSM - DTM \quad (11)$$

When $PSA > 0$, the pixel was set to the part of the potential shrub area. Then, the open operation was used to address the “salt and pepper” issue again.

In the results of OOF, many large flat protrusions also had good vegetation coverage, but not our target shrubs. In this study, the ratio of maximum height to the polygon area was used to eliminate this interference. Thus, the data were transformed into polygons firstly. Then, the maximum height (maximum PSA) and the area (Area) were computed in each polygon. Finally, the ratio (μ) of maximum height (H_{max}) to Area is used to filter:

$$\mu = \frac{H_{max}}{Area} \quad (12)$$

According to statistical analysis, for most shrub areas, the μ was usually less than 0.2 mm^{-2} , so this figure was used as the threshold for dividing shrubs and surface protrusions. Thus, when $\mu > 0.2 \text{ mm}^{-2}$, it was considered that this polygon was just a surface bulge, not a shrub, and when $\mu < 0.2 \text{ mm}^{-2}$, this polygon was extracted as the final shrub area, as shown in Figure 4d. The reason why some shrubs (mostly small shrubs) were not included in Figure 4d is that small shrubs were not sensitive in DSM because some were too small to be detected in DSM and others were excluded by mistake in DTM generation.

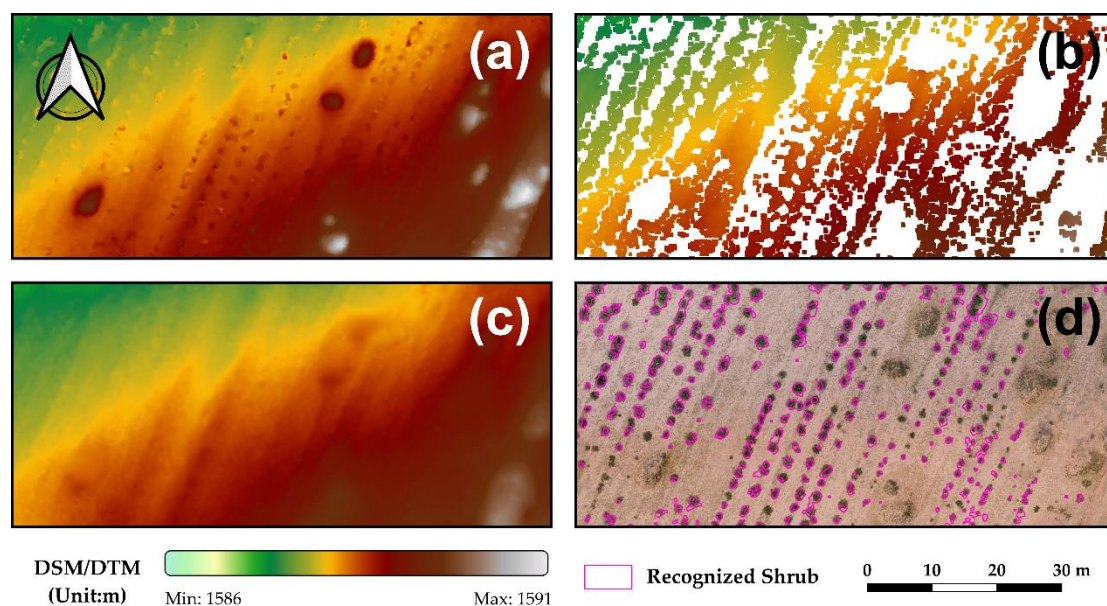


Figure 4. DSM-DTM based shrub identification approach: (a) DSM; (b) ground DTM; (c) fill DTM; (d) shrub area.

4.3. Combination and Counting

4.3.1. Combination of Shrub Areas

To combine shrub areas identified by OOF and DSM-DTM, CODA uses overlay analysis of vector data to integrate all overlapping polygons according to Table 2. When a polygon was identified by OOF as shrubs, but the area was less than 0.2 m², this area could not always be extracted by DSM-DTM, because the DSM in this study was insensitive to small objects. After the authors checked the key points for aerial triangulation, the essential reason for the insensitivity was that the substantial homogeneity in the shrubs led to errors in automatic recognition of the key points. Thus, those kinds of small regions were considered as a shrub area in CODA, which improved the accuracy of identification.

Table 2. Combination reference table of shrub areas identified by OOF and DSM-DTM.

OOF Recognized Shrub	DSM-DTM Recognized Shrub	CODA Recognized Shrub
Yes	Yes	Yes
No	Yes	No
Yes	No	if Area < 0.2 m ² then Yes if Area > 0.2 m ² then No
No	No	No

4.3.2. Shrub Counting

Because shrubs are usually quasi-circle objects in orthophoto images, Hough circles were used to count the shrub number in the shrub area image, which was developed by OpenGL with C++ API in this study. Concisely, Hough circles is an algorithm which uses Hough transform to fit the edges of circular objects and completes the detection of circular objects by judging the accumulation degree of intersection points. This algorithm not only can recognize the circle models of shrubs but also output the circle centers, which can represent the centers of shrubs. In an area with dense shrubs, Hough circles detection algorithm could always wrongly identify circles in non-shrub areas with a very high probability, so this study removed the circles in non-shrub areas and generated the final shrub count results. The Hough circles detection method and the parameter settings of the main algorithms used in this paper are shown in Table 3.

Table 3. The parameter settings of the main algorithms used in this paper.

Algorithms	Parameters	Values
Hough Circles	Method	HOUGH_GRADIENT
	Accumulator Resolution	15
	Required Separation	30
	Upper Canny Threshold	50
	Unnormalized Accumulator Threshold	30
	Smallest Radius to Consider	0
	Largest Radius to Consider	60
Multiresolution Segmentation	Scale Parameter	80
	Shape	0.4
	Compactness	0.5
DTM Filter	Search Radius	2
	Approx. Terrain Slope	0.5
Multilevel B-Spline Interpolation	Threshold Error	0.0001
	Maximum Level	11
Open Operation	Kernel	5 for threshold classification result; 15 for Ground DTM and SA.

4.4. Accuracy Assessment

To ensure and control the quality of DOMs and DSMs involved in CODA analysis, the root mean square error (RMSE) indicator was chosen to verify the accuracy of DOMs and DSMs from both

horizontal and vertical aspects [48]. The calculation formulas of horizontal RMSE (h-RMSE), vertical RMSE (v-RMSE) and overall RMSE (RMSE) are as follows:

$$h\_RMSE = \sqrt{\frac{1}{2 \cdot m} \cdot \sum_{i=1}^m [(E_{x,i})^2 + (E_{y,i})^2]} \quad (13)$$

$$v\_RMSE = \sqrt{\frac{1}{m} \cdot \sum_{i=1}^m (E_{z,i})^2} \quad (14)$$

$$RMSE = \sqrt{\frac{1}{3 \cdot m} \cdot \sum_{i=1}^m [(E_{x,i})^2 + (E_{y,i})^2 + (E_{z,i})^2]} \quad (15)$$

where x and y indicate the two directions in horizontal space, z indicates the vertical direction, $E_{x,i}$, $E_{y,i}$ and $E_{z,i}$ refer to the bias between each GPS-derived point and the corresponding point (point-pair) in the image in three directions respectively. Additionally, i indicates point-pair number, m is the count of point-pairs in each image.

To verify the shrub identification results, the shrubs in all areas of the GGA were extracted manually. These shrub locations were compared with the results of shrub identification algorithms (OOF, DSM-DTM, and CODA), and the commission errors (CE), omission errors (OE) and overall accuracy (OA) were calculated. To verify the identification ability of CODA on the TSA and DSA, 200 random samples in TSA and DSA were selected respectively for accuracy analysis.

To study the influencing factors of the CODA accuracy, 49 equal-area regions (100 m × 100 m) were generated by the grid tool of QGIS 3.2 in the GGA to analyze the regional differences. The number of shrubs and the accuracy of CODA were calculated for each region to examine how the shrub distribution affected the CODA accuracy by linear regression.

4.5. Scale Effect Analysis

To determine the best resolution of the UAS image required for shrub identification, images in different ground sampling distances (GSDs) were analyzed and compared with shrub identification accuracy and information entropy. In this paper, 3, 15, 27, 39 and 51 cm were selected by the interval of 4 cm from the minimum GSD to 51 cm where shrubs are no longer clearly visible in images.

The information entropy calculation is illustrated in Formula 6 in Section 4.1.2. For the whole image, high entropy means there is a lot of useless information, which could cause a long computational time for shrub identification. With higher GSD, the information contained in the image should be larger, because many details might be submerged in mixed pixels. Then, the objective in this analysis was to find the best GSD when there was enough information for shrub identification, and the image size was as low as possible. This method is used and discussed by many scholars [49,50]. Therefore, comparison of entropy and accuracy could address the above issue.

Because there are not full images in every GSD, the UAS images, of which resolution is above 3 cm, was reproduced by the average up-scale method. Specifically, each mixed pixel was the average of all covered pixels at a lower GSD.

5. Results

5.1. Accuracy of DOMs and DSMs

The evaluation results are shown in Table 4. The results show that the errors of sample points in UAS images were relatively small, and the RMSEs were lower than 0.01 m in the three test areas, in which the images could be used as the input source of the shrub speech recognition algorithm.

Table 4. The root mean square errors (RMSEs) in each UAS imagery used in this study.

Test Area	Point-Pair Count	h-RMSE (m)	v-RMSE (m)	RMSE (m)
GGA	4	0.009	0.008	0.009
TSA	4	0.006	0.003	0.005
DSA	3	0.006	0.005	0.006

5.2. Accuracy of Shrub Identification

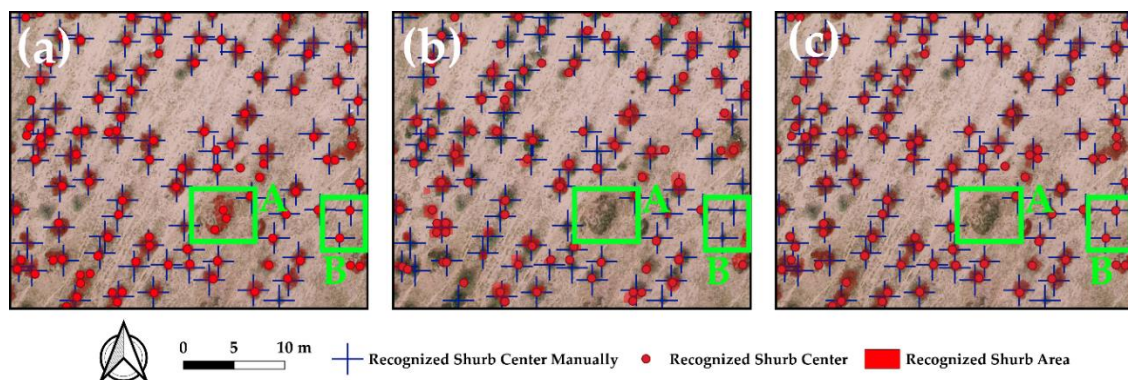
5.2.1. Comparison of Accuracy between CODA, OOF, and DSM-DTM

Compared with OOF and DSM-DTM algorithms, CODA had apparent advantages in the accuracy assessment. As shown in Table 5, the accuracy of DSM-DTM and OOF were 78.4% and 84.52%, respectively, while the accuracy of CODA was 89.96%, which was about 5% higher than OOF. Due to the limitation of DSM on the identification of small shrubs, the omission error of it was as high as 18.62%. Moreover, something like exposed rock protrusions was the main misclassification by DSM-DTM, because the μ filter was used to effectively filter other interference factors. As a result, the commission error of DSM-DTM was 3.74%. On the contrary, the OOF had a small omission error but a significant commission error due to the spectral interference of many well-growing grasslands (such as small grasslands at terrain-depression). The effective integration of DSM-DTM and OOF reduced the probability of commission and omission (both below 6%), so the overall accuracy of CODA was effectively improved.

Table 5. Errors and accuracy of the results by OOF, DSM-DTM, and CODA (test in the GGA).

Method	Sample Count	Recognized Count	Commission Errors	Omission Errors	Overall Accuracy
DSM-DTM	25963	22,100	3.74%	18.62%	78.44%
OOF		27,367	11.32%	5.91%	84.52%
CODA		25,642	4.63%	5.87%	89.96%

To further analyze the factors of accuracy improvement of CODA, a typical region was selected as shown in Figure 5, where point A contains a terrain protrusion and point B contains smaller shrubs. For point A, OOF misclassified the protrusion into three shrubs because its spectral characteristics were similar to those of the visible band. On contrast, DSM-DTM had a μ filtering mechanism, so the above interference was effectively extracted. For point B, there are two smaller shrubs at this point, which were too small therefore that they could not be effectively distinguished by DSM-DTM. Therefore, this kind of shrub relies entirely on the results of OOF to reduce the misclassification. In the CODA results, the identification results in points A and B were very similar to those with manual labeling, as shown in Figure 5c.

**Figure 5.** Shrub Identification Results in A Sample Area by: (a) OOF; (b) DSM-DTM; (c) CODA.

5.2.2. Influencing Factors of the CODA Accuracy

The CODA accuracy in different regions of the GGA was not very significant, as shown in Figure 6a, ranging from 86.7% to 93.2% (standard deviation: 1.44%). Since the GGA covers shrubs in different growth stages and different sizes, CODA had a vigorous ability to recognize various shrubs. The linear regression result is shown in Figure 6b: as the shrub count increased, the accuracy variation became lower continuously, and the accuracy had an inevitable downward trend (where the slope was -9.55). For example, the standard deviation of the CODA accuracy in the GGA below 500 shrubs was 1.97%, and average accuracy was 90.21%, whereas the standard deviation of the accuracy in the area above 500 shrubs was 1.12%, and average accuracy was 89.85%. This phenomenon was most likely because the likelihood of contiguous shrubs increased with the increase of shrubs, and the Hough circles detection method was challenging to count correctly, which resulted in a decrease in the CODA accuracy.

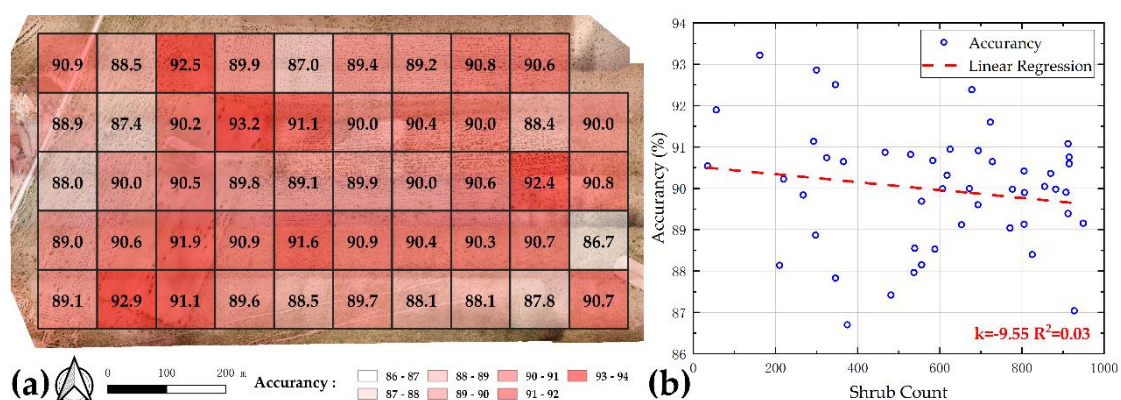


Figure 6. Accuracy analysis in the GGA: (a) accuracy of each region; (b) the relationship between accuracy and shrub count.

5.3. Shrub Identification of the TSA and DSA

5.3.1. Accuracy Analysis

The accuracy results showed that there were 25 and 15 commissions in TSA and DSA respectively, and the extraction accuracy of the DSA was significantly higher than that of the TSA, which may be due to the more complex shrub distribution in typical grasslands, as shown in Table 6.

Table 6. Accuracy of CODA shrub identification results in the TSA and DSA.

Location	Recognized Count	Sample Count	Commission Count	Accuracy
TSA	576	200	25	87.5%
DSA	2518	200	15	92.5%

5.3.2. Distribution Characteristics of Shrubs in the TSA and DSA

To further analyze the results of shrub extraction, the grid tool of QGIS 3.2 was used to divide the DSA and TSA into 11 and 26 equal-area regions respectively ($100\text{ m} \times 100\text{ m}$ grids). As shown in Figure 7, there were significant differences: (1) Difference in quantity: shrubs in the TSA ranged from 31 to 75 per grid (average of 52.82 per grid), while shrubs in the DSA ranged from 72 to 119 per grid (average of 96.84 per grid). Therefore, the average shrub density of the DSA was 83.4% higher than that of the TSA. (2) Differences in distribution: the coefficient of variation of the TSA was 0.27, while the coefficient of variation of the DSA was 0.14, so the shrub distribution in the TSA region was more diverse, which was also likely to be related to the complexity of community structure and shrub distribution in typical grasslands.

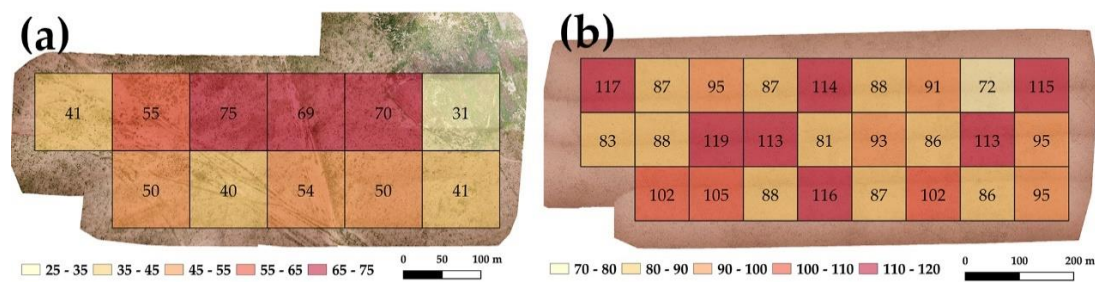


Figure 7. Shrub counts of each region in the (a) TSA; (b) DSA.

5.4. Scale Effect of Shrub Identification

The relationship between the CODA accuracy and image information entropy of UAS images in different GSD is shown in Figure 8. For the GGA, when the resolution was between 3 and 15 cm, the information entropy decreased continuously, with a minimum value of 5.42, while the precision decreased slightly, only about 0.13%. When the resolution declined to 15 cm or lower, the information entropy then rose linearly to 5.66 at 27 cm and then remained flat, but the accuracy dropped rapidly. Therefore, the resolution of the best observation of GGA was about 15 cm.

For the TSA, as the gradual decrease of resolution, the information entropy kept stable between 5.7 and 5.75, with little change. However, the degradation of identification accuracy was speedy, from 87.52% of 3 cm to 82.13% of 51 cm. This is likely to be related to the complexity of typical grasslands. Moreover, the stability of the entropy indicated that the image was always at a certain complexity, and the rapid decrease in accuracy indicated that the resolution of the best observation in the TSA was below 3 cm.

For the DSA, when the resolution was between 3 and 51 cm resolution, the information entropy increased from 4.84 to 4.97. However, the accuracy drop was not fast, just from 92.31% to 91.31%, only about one percentage point. This illustrates two issues: on the one hand, because the ecosystem structure of the desert steppe is relatively simple, the recognition accuracy maintained a high state; on the other hand, due to the formation of a large number of mixed pixels, the spatial difference was continuously weakened. As a result, the entropy of the TSA was constantly increasing as the resolution decreased. Therefore, the optimal resolution of the DSA was below 3 cm, but increasing the resolution may not significantly improve the recognition accuracy.

The best GSD for shrub identification in different regions was probably due to differences in the complexity of the distribution and size of shrubs and environmental disturbances. For the GGA, because the ecosystem of it is simple, the shrubs are artificially planted and arranged regularly, the best observation accuracy was as high as 15 cm, much larger than that of the TSA and DSA. Due to the influence of natural conditions and human disturbance, the ecosystem complexity of the TSA and DSA is more complicated, so the best observation accuracy was relatively small (less than 3 cm).

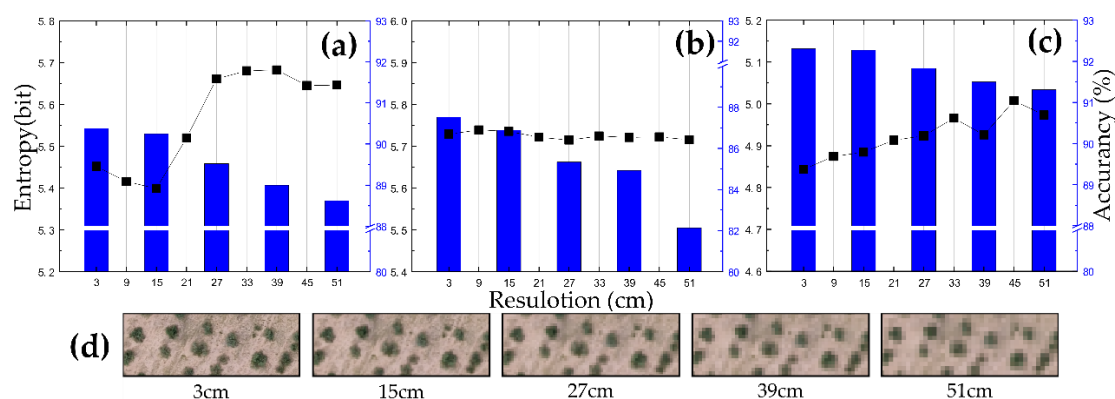


Figure 8. Shrub identification accuracy and information entropy of images at different resolution in (a) the GGA; (b) the TSA; (c) the DSA. (d) A sample region of the GGA in different resolutions.

6. Discussion

6.1. Uncertainties, Errors, and Accuracies

From the above analysis, CODA can make up for the deficiency of OOF and DSM-DTM in shrub identification. In this study, three kinds of interference factors were extracted: bare highland/rocks, depression, and highland, respectively (Figure 9): (1) Bare highland/rocks: bare surface protrusions can interfere with the results of DSM-DTM algorithm, but can be easily eliminated by OOF. (2) Depression: small pieces of grasslands in terrain-depression often means better hydrological conditions, so its ExG-ExR value always seems larger, which will interfere with the results of OOF. While no protrusions will be formed in the DSM-DTM in terrain-depression area this kind of interference can be eliminated. (3) Highland: these kind of surface protrusions tend to have a small slope in edges, so they can be filtered by the ratio of the maximum height to the area (μ filter in this paper). Therefore, the above several interference factors are effectively extracted in the algorithm (CODA) proposed in this study, so the results are more in line with the real situation.

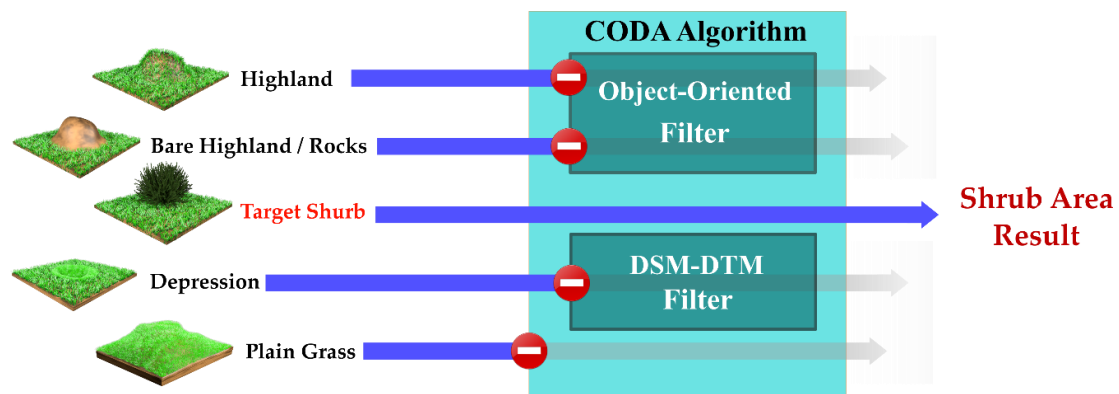


Figure 9. Why is the accuracy of CODA is higher than that of OOF and DSM-DTM?

In this paper, structure from motion (SfM) and multi-view stereopsis (MVS) technology were used to analyze UAS images in shrub-encroached grassland area, to produce point cloud data with sufficient density and then produce DSM [51,52]. In the above process, the overlap and multi-angle photography of UAS images become the direct influence factors of point cloud density [53,54]. Therefore, in addition to the apparent influence of height above ground level (AGL) on the shrub recognition accuracy, overlap rate and multi-angle photography were also significant covariates affecting the recognition accuracy. Currently, many scholars have also used SfM and MVS technology to carry out accuracy analysis [55–57]. Georg et al. retrieve and identify sward height by UAS remote sensing under the assumption of crop surface models (also known as CSM) [58].

Under the largely fixed height and overlap rate set by our experiment, the average point cloud densities for DSM production exceeded 1000 points·m⁻², which were enough for shrub identification. However, there was no multi-angle photography in our experiment, only vertical downward shooting. For the shrub model in the Mongolian Plateau, how much improvement of DSM accuracy can be achieved by choosing multi-angle capturing is an essential issue in future research. At present, the variability of point cloud density is considerable (the standard deviation in the GGA was 56.21 point·m⁻², while the standard deviation of the TSA was 159.73 point·m⁻², see Table 1). Nevertheless, the information of shrub structure can be supplemented by multi-angle photography, which might improve the stability of point cloud density.

In addition, the bands were not normalized before the ExG-ExR computation. But we still believe that our methods and results have a certain meaning. On the one hand, our goal was to identify the shrubs, so slight color differences do not have a significant impact on accuracy. On the other hand, we chose clear cloudless mornings to collect images, and camera parameters, such as aperture, ISO,

were fixed to make the whole images homogeneous and reliable. Moreover, there were no GCPs used in DSM/DOM production. However, for more reliable and scientific analysis, we will pay attention to these issues in future research.

6.2. The Contrast of Several Different Recognition Methods for Shrubs

The CODA, OOF and DSM-DTM algorithms were compared with the current popular shrub extraction algorithms in remote sensing. As shown in Table 7, the accuracy of CODA (89.96%) was second only to the semi-manual labeling used by Goslee (95%) [13] and was similar to the accuracy of the method used by Dong to combine object-oriented extraction with support vector machine (SVM) [59]. The high precision of CODA depends mainly on two reasons: (1) Full use of multiple dimensional information: CODA makes full use of the various information that can be extracted by UAS remote sensing, especially using surface elevation data, which is not used in other studies. Also, the single accuracy of OOF (84.52%) and DSM-DTM (78.44%) was lower than that of CODA, which means DSM-DTM could make up for the shortcomings of OOF. So, CODA has the advantage of higher precision. (2) High resolution of UAS data: The spatial resolution (0.02 m) of the image data used in this study was much higher than other research. Therefore, compared with others using high-resolution satellite remote sensing data, the proposed CODA algorithm is more suitable for shrub-encroached grassland and grassland degradation research on smaller scales (e.g., farms, villages).

Table 7. The contrast of several different recognition methods for shrubs.

Algorithm	Source	Res. (m)	Involved Dimension			Accuracy	Ref.
			Spe.	Alt.	Mor.		
Object-Oriented Method	Quick Bird	0.61	√	-	√	87%	[31]
Object-Oriented Method and SVM	ZY-3	5.8	√	-	√	89.24%	[59]
Semi-Manual	Aerial Photograph and Satellite Images	-	√	-	√	95%	[13]
OOF	UAS	0.02	√	-	√	84.52%	-
DSM-DTM	UAS	0.02	-	√	-	78.44%	-
CODA	UAS	0.02	√	√	√	89.96%	-

"Res." refers to resolution; "Spe." refers to spectrum; "Alt." refers to altitude; "Mor." refers to morphology; "Ref." refers to Reference.

6.3. Prospective

In this study, the research carried out accuracy verification and quantitative statistical analysis of desert steppe and typical steppe based on the CODA method. Also, it can be further used to study shrub-encroached grassland mechanism or grassland degradation in the Mongolian Plateau through regional statistics, regional topology, and shrub structure.

- (1) **Regional Statistics:** For the shrub-encroached grassland, in addition to counting the number of shrubs, it can also be analyzed through various aspects such as shrub area statistics and shrub size statistics. The shrub sizes and shrub areas, to some extent, reflect the stage of the process of shrub-encroached process. Under the same climatic conditions, generally smaller shrubs probably mean that the beginning time of shrub-encroachment in this area is relatively short. Also, the difference in shrub size and shrub area may also indicate that grassland pressure in this area is more persistent than that in areas with less difference.
- (2) **Regional Topology:** Many scholars have analyzed the distribution characteristics of shrubs, such as random distribution, cluster distribution, etc. [60,61]. Therefore, the average spacing between shrubs and their differences can reflect the community structure of the shrubs, the path of seed propagation, to some extent, reflect the mechanism of the shrub-encroached process.
- (3) **Shrub Structure:** The morphological structure and spectral characteristics of shrubs with different production mechanisms may also differ. Figure 10a is the ideal shrub model, which was also the

shrub model assumed in this paper. As a result, the ExG-ExR of the ideal shrub is homogeneous. Because other grasslands often form mixed pixels with bare soil, the ExG-ExR of shrubs is larger than the other grassland. However, the actual formation of shrubs usually has different formation mechanisms: for example, in Figure 10b, the *Stipa Grandis* is occupied by herbs after being eaten by the animals, and the surrounding soil is weathered and denuded, which causes the bulge of the earth's surface. Due to long-term wind direction and other factors, its ExG-ExR is inconsistent in all directions. That is to say, the bidirectional reflectance distribution function (BRDF) of this shrub has a positive correlation with the formation mechanism of the shrub. Based on CODA, combined with the above features, the shrub-encroached mechanism can be further analyzed.

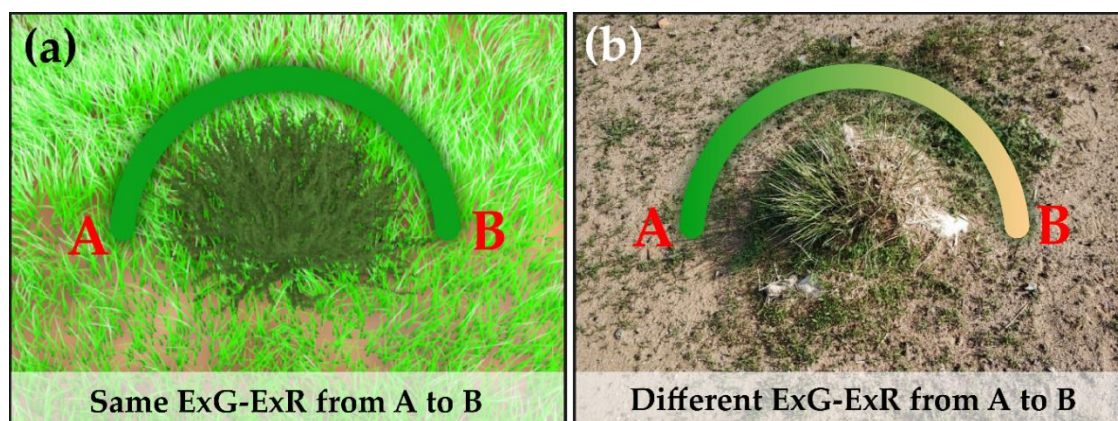


Figure 10. ExG-ExR directional heterogeneity of (a) the ideal model; (b) a practical situation of shrub-encroached grassland.

7. Conclusions

The object-oriented filter algorithm and the DSM-DTM terrain analysis algorithm were combined to make full use of the DOMs and DSMs of UAS remote sensing to establish a high-accuracy automatic shrub identification algorithm, namely CODA. In this paper, CODA was used in the shrub identification of two test areas of typical and desert steppe in the Mongolian Plateau. Then, the information entropy theory was used to analyze the scale effect of UAS remote sensing in shrub identification. The results showed that CODA had high-accuracy performance, specifically:

- (1) The overall accuracy of CODA was 89.96% in the Grain for Green test area (GGA), which was higher than a single OOF algorithm (accuracy: 84.52%) or DSM-DTM algorithm (accuracy: 78.44%). This was because CODA could combine the advantages of the above two methods mostly. Specifically, CODA could effectively eliminate interference factors such as shrub-like highland and well-grown grassland in terrain-depression area. Also, the CODA identification performance was related to the shrub density: as the density increased, the accuracy decreased slightly.
- (2) CODA was adaptable to the typical steppe test area (TSA) and the desert steppe test area (DSA), in which the shrub identification accuracy was 87.5% and 92.5%, respectively. Especially, shrub density of the TSA was smaller, and the regional difference of the TSA was more significant, which was likely to be related to the higher community structure complexity of typical steppe.
- (3) The ground sampling distance of the best observation of the GGA was about 15 cm, while it was below 3 cm in the typical and desert steppe test area. However, increasing image resolution in the DSA may not improve the identification accuracy significantly.

Author Contributions: Conceptualization, Y.D.; data curation, Y.D. and N.W.; methodology, H.Y. and Y.H.; resources, M.H.; software, Y.D.; supervision, H.Y. and M.H.; validation, N.W.; visualization, N.W.; writing—original draft, Y.D.; writing—review and editing, H.Y., N.W., M.H. and Y.H.

Funding: This research was funded by the Strategic Priority Research Program of the Chinese Academy of Sciences (XDA23100202), National Natural Science Foundation of China (41671517).

Acknowledgments: We would like to thank Xin Wen and Xingguang Ma for their support in the field. Also, we would like to thank the four anonymous reviewers for their constructive comments.

Conflicts of Interest: The authors declare no conflict of interest.

References

- Chen, L.; Li, H.; Zhang, P.; Zhao, X.; Zhou, L.; Liu, T.; Hu, H.; Bai, Y.; Shen, H.; Fang, J. Climate and native grassland vegetation as drivers of the community structures of shrub-encroached grasslands in Inner Mongolia, China. *Landsc. Ecol.* **2014**, *30*, 1627–1641. [[CrossRef](#)]
- Daryanto, S.; Eldridge, D.J. Plant and soil surface responses to a combination of shrub removal and grazing in a shrub-encroached woodland. *J. Environ. Manag.* **2010**, *91*, 2639–2648. [[CrossRef](#)] [[PubMed](#)]
- Bai, Y.; Han, X.; Wu, J.; Chen, Z.; Li, L. Ecosystem stability and compensatory effects in the Inner Mongolia grassland. *Nature* **2004**, *431*, 181–184. [[CrossRef](#)] [[PubMed](#)]
- Jiang, G.; Han, X.; Wu, J. Restoration and management of the Inner Mongolia grassland require a sustainable strategy. *AMBIO A J. Hum. Environ.* **2006**, *35*, 269–271. [[CrossRef](#)] [[PubMed](#)]
- Bazha, S.N.; Danzhalova, E.V.; Kazantseva, T.I.; Gunin, P.D. Influence of grazing on morphometric characteristics of principal dominants in phytocenoses of steppe ecosystems in Central Mongolia. *Ботанический журнал* **2009**, *94*, 1505–1526.
- Chen, S.P.; Bai, Y.F.; Lin, G.H.; Liang, Y.; Han, X.G. Effects of grazing on photosynthetic characteristics of major steppe species in the Xilin River Basin, Inner Mongolia, China. *Photosynthetica* **2005**, *43*, 559–565. [[CrossRef](#)]
- Steffens, M. Destabilization of SOM Following Overgrazing and Aggregate Deterioration in a Steppe Ecosystem in Inner Mongolia (China). *J. Beliefs Values* **1998**, *19*, 83–96.
- Zhan, W.; Deng, X.; Wei, S.; Li, Z.; Chen, J. What is the main cause of grassland degradation? A case study of grassland ecosystem service in the middle-south Inner Mongolia. *Catena* **2017**, *150*, 100–107.
- Fan, Y.; Li, X.-Y.; Li, L.; Wei, J.-Q.; Shi, F.-Z.; Yao, H.-Y.; Liu, L. Plant Harvesting Impacts on Soil Water Patterns and Phenology for Shrub-encroached Grassland. *Water* **2018**, *10*, 736. [[CrossRef](#)]
- Li, X.-Y.; Zhang, S.-Y.; Peng, H.-Y.; Hu, X.; Ma, Y.-J. Soil water and temperature dynamics in shrub-encroached grasslands and climatic implications: Results from Inner Mongolia steppe ecosystem of north China. *Agric. For. Meteorol.* **2013**, *171*–172, 20–30. [[CrossRef](#)]
- Lin, X.-R. Study on shrub community diversity of Ordos Plateau, Inner Mongolia, Northern China. *J. Arid Environ.* **2001**, *47*, 271–279. [[CrossRef](#)]
- Zhao, H.-L.; Zhou, R.-L.; Su, Y.-Z.; Zhang, H.; Zhao, L.-Y.; Drake, S. Shrub facilitation of desert land restoration in the Horqin Sand Land of Inner Mongolia. *Ecol. Eng.* **2007**, *31*, 1–8. [[CrossRef](#)]
- Goslee, S.C.; Havstad, K.M.; Peters, D.P.C.; Rango, A.; Schlesinger, W.H. High-resolution images reveal rate and pattern of shrub encroachment over six decades in New Mexico, U.S.A. *J. Arid Environ.* **2003**, *54*, 755–767. [[CrossRef](#)]
- Jackson, D.S.; Murdoch, J.D.; Mandakh, B. Habitat Classification Using Landsat 7ETM+ Imagery of the Ikh Nart Nature Reserve and Surrounding Areas in Dornogobi and Dundgobi Aimags, Mongolia. *Mong. J. Biol. Sci.* **2006**, *4*, 33–40.
- John, R.; Chen, J.; Lu, N.; Guo, K.; Liang, C.; Wei, Y.; Noormets, A.; Ma, K.; Han, X. Predicting plant diversity based on remote sensing products in the semi-arid region of Inner Mongolia. *Remote Sens. Environ.* **2008**, *112*, 2018–2032. [[CrossRef](#)]
- Everaerts, J. The use of unmanned aerial vehicles (UAVs) for remote sensing and mapping. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2008**, *37*, 1187–1192.
- Rey, N.; Volpi, M.; Joost, S.; Tuia, D. Detecting animals in African Savanna with UAVs and the crowds. *Remote Sens. Environ.* **2017**, *200*, 341–351. [[CrossRef](#)]
- Jin, X.; Liu, S.; Baret, F.; Hemerlé, M.; Comar, A. Estimates of plant density of wheat crops at emergence from very low altitude UAV imagery. *Remote Sens. Environ.* **2017**, *198*, 105–114. [[CrossRef](#)]

19. Gini, R.; Sona, G.; Ronchetti, G.; Passoni, D.; Pinto, L. Improving Tree Species Classification Using UAS Multispectral Images and Texture Measures. *ISPRS Int. J. Geo-Inf.* **2018**, *7*, 315. [\[CrossRef\]](#)
20. Possoch, M.; Bieker, S.; Hoffmeister, D.; Bolten, A.; Schellberg, J.; Bareth, G. Multi-temporal crop surface models combined with the RGB vegetation index from UAV-based images for forage monitoring in grassland. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2016**, *41*, 991–998. [\[CrossRef\]](#)
21. Lu, B.; He, Y. Species classification using Unmanned Aerial Vehicle (UAV)-acquired high spatial resolution imagery in a heterogeneous grassland. *ISPRS J. Photogramm. Remote Sens.* **2017**, *128*, 73–85. [\[CrossRef\]](#)
22. Stow, D.; Lippitt, C.; Coulter, L.; Loerch, A. Towards an end-to-end airborne remote-sensing system for post-hazard assessment of damage to hyper-critical infrastructure: Research progress and needs. *Int. J. Remote Sens.* **2018**, *39*, 1441–1458. [\[CrossRef\]](#)
23. Gini, R.; Passoni, D.; Pinto, L.; Sona, G. Use of Unmanned Aerial Systems for multispectral survey and tree classification: A test in a park area of northern Italy. *Eur. J. Remote Sens.* **2014**, *47*, 251–269. [\[CrossRef\]](#)
24. Gupta, S.G.; Ghonge, M.M.; Jawandhiya, P. Review of unmanned aircraft system (UAS). *Int. J. Adv. Res. Comput. Eng. Technol.* **2013**, *2*, 1646–1658.
25. Lippitt, C.; Zhang, S. The impact of small unmanned airborne platforms on passive optical remote sensing: A conceptual perspective. *Int. J. Remote Sens.* **2018**, *39*, 1–17. [\[CrossRef\]](#)
26. Von Bueren, S.K.; Burkart, A.; Hueni, A.; Rascher, U.; Tuohy, M.P.; Yule, I.J. Deploying four optical UAV-based sensors over grassland: Challenges and limitations. *Biogeosciences* **2015**, *12*, 163–175. [\[CrossRef\]](#)
27. Yu, N.; Li, L.; Schmitz, N.; Tian, L.F.; Greenberg, J.A.; Diers, B.W. Development of methods to improve soybean yield estimation and predict plant maturity with an unmanned aerial vehicle based platform. *Remote Sens. Environ.* **2016**, *187*, 91–101. [\[CrossRef\]](#)
28. Meyer, G.E.; Neto, J.C. Verification of color vegetation indices for automated crop imaging applications. *Comput. Electron. Agric.* **2008**, *63*, 282–293. [\[CrossRef\]](#)
29. Le, V.N.T.; Apopei, B.; Alameh, K. Effective plant discrimination based on the combination of local binary pattern operators and multiclass support vector machine methods. *Inf. Process. Agric.* **2019**, *6*, 116–131.
30. Li, B.; Xu, X.; Han, J.; Zhang, L.; Bian, C.; Jin, L.; Liu, J. The estimation of crop emergence in potatoes by UAV RGB imagery. *Plant Methods* **2019**, *15*, 15. [\[CrossRef\]](#)
31. Laliberte, A.S.; Rango, A.; Havstad, K.M.; Paris, J.F.; Beck, R.F.; McNeely, R.; Gonzalez, A.L. Object-oriented image analysis for mapping shrub encroachment from 1937 to 2003 in southern New Mexico. *Remote Sens. Environ.* **2004**, *93*, 198–210. [\[CrossRef\]](#)
32. Zhang, W.; Yang, X.; Manlike, A.; Jin, Y.; Zheng, F.; Guo, J.; Shen, G.; Zhang, Y.; Xu, B. Comparative study of remote sensing estimation methods for grassland fractional vegetation coverage—a grassland case study performed in Ili prefecture, Xinjiang, China. *Int. J. Remote Sens.* **2019**, *40*, 2243–2258. [\[CrossRef\]](#)
33. Guo, J.; Yang, X.; Niu, J.; Jin, Y.; Xu, B.; Shen, G.; Zhang, W.; Zhao, F.; Zhang, Y. Remote sensing monitoring of green-up dates in the Xilingol grasslands of northern China and their correlations with meteorological factors. *Int. J. Remote Sens.* **2019**, *40*, 2190–2211. [\[CrossRef\]](#)
34. Nex, F.; Remondino, F. UAV for 3D mapping applications: A review. *Appl. Geomat.* **2014**, *6*, 1–15. [\[CrossRef\]](#)
35. Mousa, Y.A.; Helmholtz, P.; Belton, D. New Dtm Extraction Approach from Airborne Images Derived Dsm. *ISPRS—Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2017**, *XLII-1/W1*, 75–82. [\[CrossRef\]](#)
36. Waser, L.T.; Baltsavias, E.; Ecker, K.; Eisenbeiss, H.; Ginzler, C.; Küchler, M.; Thee, P.; Zhang, L. High-resolution digital surface models (DSMs) for modelling fractional shrub/tree cover in a mire environment. *Int. J. Remote Sens.* **2008**, *29*, 1261–1276. [\[CrossRef\]](#)
37. Riaño, D.; Chuvieco, E.; Ustin, S.L.; Salas, J.; Rodríguez-Pérez, J.R.; Ribeiro, L.M.; Viegas, D.X.; Moreno, J.M.; Fernández, H. Estimation of shrub height for fuel-type mapping combining airborne LiDAR and simultaneous color infrared ortho imaging. *Int. J. Wildland Fire* **2007**, *16*, 341–348. [\[CrossRef\]](#)
38. Bellakout, A.; Cherkaoui, M.; Ettarid, M.; Touzani, A. Automatic 3D Extraction of Buildings, Vegetation and Roads from LIDAR Data. *ISPRS—Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2016**, *XLI-B3*, 173–180. [\[CrossRef\]](#)
39. Sohn, G.; Dowman, I. Data fusion of high-resolution satellite imagery and LiDAR data for automatic building extraction. *ISPRS J. Photogramm. Remote Sens.* **2007**, *62*, 43–63. [\[CrossRef\]](#)

40. Michez, A.; Lejeune, P.; Bauwens, S.; Herinaina, A.A.L.; Blaise, Y.; Castro Muñoz, E.; Lebeau, F.; Bindelle, J. Mapping and Monitoring of Biomass and Grazing in Pasture with an Unmanned Aerial System. *Remote Sens.* **2019**, *11*, 473. [[CrossRef](#)]
41. Stroppiana, D.; Villa, P.; Sona, G.; Ronchetti, G.; Candiani, G.; Pepe, M.; Busetto, L.; Migliazzi, M.; Boschetti, M. Early season weed mapping in rice crops using multi-spectral UAV data. *Int. J. Remote Sens.* **2018**, *39*, 5432–5452. [[CrossRef](#)]
42. Melville, B.; Lucieer, A.; Aryal, J. Classification of Lowland Native Grassland Communities Using Hyperspectral Unmanned Aircraft System (UAS) Imagery in the Tasmanian Midlands. *Drones* **2019**, *3*, 5. [[CrossRef](#)]
43. Haala, N.; Cramer, M.; Weimer, F.; Trittler, M. Performance test on UAV-based photogrammetric data collection. *Proc. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2011**, *38*, 7–12. [[CrossRef](#)]
44. Remondino, F.; Barazzetti, L.; Nex, F.; Scaioni, M.; Sarazzi, D. UAV photogrammetry for mapping and 3d modeling—current status and future perspectives. *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci.* **2011**, *38*, C22. [[CrossRef](#)]
45. Prentice, I.C.; Werger, M.J.A. Clump spacing in a desert dwarf shrub community. *Vegetatio* **1985**, *63*, 133–139. [[CrossRef](#)]
46. Institute of Standardization of Surveying and Mapping of China. *Specification for Aerial Photography of 1:500, 1:1000 and 1:2000 Scale Topographic Maps (GB/T 6962-2005)*; China Standard Press: Beijing, China, 2008; pp. 5–6.
47. Pun, T.; Pun, T. A new method for gray-level picture threshold using the entropy of the histogram. *Signal Process.* **1985**, *2*, 223–237. [[CrossRef](#)]
48. Zhang, S.; Lippitt, C.; Bogus, S.; Loerch, A.; Sturm, J. The accuracy of aerial triangulation products automatically generated from hyper-spatial resolution digital aerial photography. *Remote Sens. Lett.* **2015**, *7*, 160–169. [[CrossRef](#)]
49. Han, P.; Gong, J.; Li, Z.; Bo, Y.; Cheng, L. Selection of optimal scale in remotely sensed image classification. *J. Remote Sens.* **2010**, *14*, 507–518.
50. Jian, L.; Man, P.; Xin, L. Information entropy of remote sensing images and its applications in image fusion. In Proceedings of the Remote Sensing of the Environment: 15th National Symposium on Remote Sensing of China, Guiyan City, China, 9 June 2006. [[CrossRef](#)]
51. Aasen, H.; Honkavaara, E.; Lucieer, A.; Zarco-Tejada, P. Quantitative remote sensing at ultra-high resolution with UAV spectroscopy: A review of sensor technology, measurement procedures, and data correction workflows. *Remote Sens.* **2018**, *10*, 1091. [[CrossRef](#)]
52. Reitberger, J.; Schnörr, C.; Krzystek, P.; Stilla, U. 3D segmentation of single trees exploiting full waveform LIDAR data. *ISPRS J. Photogramm. Remote Sens.* **2009**, *64*, 561–574. [[CrossRef](#)]
53. Aasen, H.; Burkart, A.; Bolten, A.; Bareth, G. Generating 3D hyperspectral information with lightweight UAV snapshot cameras for vegetation monitoring: From camera calibration to quality assurance. *ISPRS J. Photogramm. Remote Sens.* **2015**, *108*, 245–259. [[CrossRef](#)]
54. Harwin, S.; Lucieer, A.; Osborn, J. The impact of the calibration method on the accuracy of point clouds derived using unmanned aerial vehicle multi-view stereopsis. *Remote Sens.* **2015**, *7*, 11933–11953. [[CrossRef](#)]
55. Näsi, R.; Viljanen, N.; Kaivosoja, J.; Alhonoja, K.; Hakala, T.; Markelin, L.; Honkavaara, E. Estimating biomass and nitrogen amount of barley and grass using UAV and aircraft based spectral and photogrammetric 3D features. *Remote Sens.* **2018**, *10*, 1082. [[CrossRef](#)]
56. Turner, D.; Lucieer, A.; Watson, C. An automated technique for generating georectified mosaics from ultra-high resolution unmanned aerial vehicle (UAV) imagery, based on structure from motion (SfM) point clouds. *Remote Sens.* **2012**, *4*, 1392–1410. [[CrossRef](#)]
57. Viljanen, N.; Honkavaara, E.; Näsi, R.; Hakala, T.; Niemeläinen, O.; Kaivosoja, J. A novel machine learning method for estimating biomass of grass swards using a photogrammetric canopy height model, images and vegetation indices captured by a drone. *Agriculture* **2018**, *8*, 70. [[CrossRef](#)]
58. Bareth, G.; Schellberg, J. Replacing Manual Rising Plate Meter Measurements with Low-cost UAV-Derived Sward Height Data in Grasslands for Spatial Monitoring. *PFG-J. Photogramm. Remote Sens. Geoinf. Sci.* **2018**, *86*, 157–168. [[CrossRef](#)]

59. Dong, Z.; Zhao, X.; Liang, D.; Huang, W.; Peng, D.; Huang, L. Remote sensing identification of shrub encroachment in grassland in Inner Mongolia. *Trans. Chin. Soc. Agric. Eng.* **2014**, *30*, 152–158.
60. Flory, S.L.; Clay, K. Invasive shrub distribution varies with distance to roads and stand age in eastern deciduous forests in Indiana, USA. *Plant Ecol.* **2006**, *184*, 131–141. [[CrossRef](#)]
61. McGlynn, I.O.; Okin, G.S. Characterization of shrub distribution using high spatial resolution remote sensing: Ecosystem implications for a former Chihuahuan Desert grassland. *Remote Sens. Environ.* **2006**, *101*, 554–566. [[CrossRef](#)]



© 2019 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<http://creativecommons.org/licenses/by/4.0/>).