THE ANALYSIS OF BURROWS RECOGNITION ACCURACY IN XINJIANG'S PASTURE AREA BASED ON UAV VISIBLE IMAGES WITH DIFFERENT SPATIAL RESOLUTION

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ABSTRACT:

The rodent disaster is one of the main biological disasters in grassland in northern Xinjiang. The eating and digging behaviors will cause the destruction of ground vegetation, which seriously affected the development of animal husbandry and grassland ecological security. UAV low altitude remote sensing, as an emerging technique with high spatial resolution, can effectively recognize the burrows. However, how to select the appropriate spatial resolution to monitor the calamity of the rodent disaster is the first problem we need to pay attention to. The purpose of this study is to explore the optimal spatial scale on identification of the burrows by evaluating the impact of different spatial resolution for the burrows identification accuracy. In this study, we shoot burrows from different flight heights to obtain visible images of different spatial resolution. Then an object-oriented method is used to identify the caves, and we also evaluate the accuracy of the classification. We found that the highest classification accuracy of holes, the average has reached more than 80%. At the altitude of 24m and the spatial resolution of 1cm, the accuracy of the classification is the highest We have created a unique and effective way to identify burrows by using UAVs visible images. We draw the following conclusion: the best spatial resolution of burrows recognition is 1cm using DJI PHANTOM-3 UAV, and the improvement of spatial resolution does not necessarily lead to the improvement of classification accuracy. This study lays the foundation for future research and can be extended to similar studies elsewhere.

1. INTRODUCTION

Xinjiang is one of the important grassland animal husbandry bases in China. It has a total area of 5,725,800 hectares of natural grassland, of which 4,860,800 hectares can be used, ranking third in the country (Yan DJ., 2015). Grassland rodent pests refer to rodents that inhabit grasslands have exceeded the environmental carrying capacity due to their high population density, which has adversely affected grassland health and animal husbandry development (Yang YP., 2016). The Yellow Steppe Lemming (*Eolagurus luteus*) is mainly distributed in northern areas in Xinjiang, and the rodent pests in Ba Yin Gou pasture in Wu Su City is the most typical. Not only do these rodents eat a large amount of the stems and leaves of plants, but also destroy their roots and seeds, seriously endangering the growth of grasses. At the same time, the rodent excavation behavior changed the physical and chemical properties of the surface soil, resulting in deep calcium deposits accumulated in the hole. This not only affects the growth of pasture, but also is vulnerable to eolian erosion, eventually causing a decrease in forage grass cover and exacerbating the desertification process in the steppe.

The traditional methods for rodent pest detection mainly include laying patterns, laying traps, and artificial observations (Sheng Z.H., 2015; Hajjaran H., 2013). Ma Yong studied the distribution and ecological habits of the Yellow Steppe Lemming in the Mu Lei County of northern Xinjiang through nearly four months of continuous field observations (Ma Y., 1982). Although this survey has yielded convincing survey results, such survey methods still require a lot of manpower and material costs, and there are also issues such as lack of timeliness and accuracy, which cannot satisfy the demand for researchers to obtain the real-time and accurate disaster information. With the development of remote sensing technology, the monitoring of rodent disaster has entered a new stage. Scholars at home and abroad used satellite images such as Landsat-8 (Li, PX., 2016), Quick Bird (Addink E.A., 2010) and SPOT-5 (Wilschut L.I., 2013) to monitor rat damage, but not as drones could obtain higher spatial resolution images.
As a new type of remote sensing method, low altitude remote sensing of drones has been widely used in landscape ecology and ecology field in recent years because of its high space, time resolution, flexible operation, and low cost (Zhang ZM., 2017). Nowadays, the use of drones for rodent disaster monitoring has only just begun. Ma Tao studied the coverage and distribution characteristics of *Rhombomys opimus* in the Gurbantunggut desert forest based on UAV images (Ma T., 2018). However, these studies have failed to compare the accuracy of burrows recognition for aerial images with different spatial resolution scales.

Based on this, this paper selected Ba Yin Gou ranch in Wu Su City as a research area, and used consumer-grade DJI PHANTOM-3 as low-altitude remote sensing platforms to

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collect images with different flying heights. In this paper, the photos were categorized and the spatial resolution of images at different altitudes was calculated. Then, based on the images of these different spatial resolutions, the burrows were identified and extracted, and the recognition accuracy was compared, which has important guiding significance for the later monitoring of rodent disasters.

2. RESEARCH AREA

The experimental area (Fig. 1) is located in Ba Yin Gou Pasture (84°59′55″E 44°12′56″N) in Wu Su City, Xinjiang, China. It is located in the semi-desert grassland, where the vegetation types are mainly *Seriphidium transiliense*, *Anabasis aphylla*, *Salsolacollina Pall* and other low-vegetation plants. Typical rodent disaster in the experimental area is Yellow Stepped Lemming (*Eolagurus luteus*).

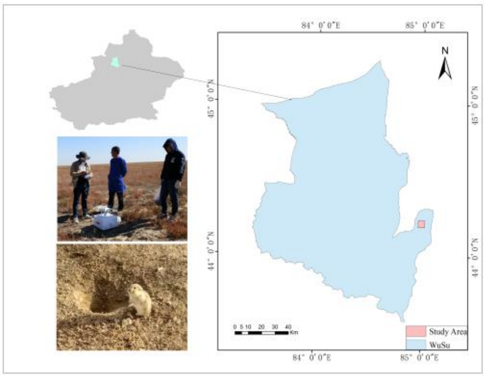

Figure 1.Study Area

3. DATA AND METHODS

3.1 Data Source

The remote sensing platform we used in this study is the DJI PHANTOM-3 UAV, with the camera type FC300S. The main wavelength range is visible light (RGB), and the detailed parameters are shown in Tab.1. The flight time is September 27, 2017. In this paper, we selected four images with flight heights of 3 meters, 6 meters, 24 meters, and 30 meters for analysis.

UAV platform	
Model	DJI PHANTOM-3
Type	Quadrotor
Weight	1280 g
Maximum flight time	20 min
Maximum flight speed	57.6km/h
Highest flight altitude	6000m
Sensor	
Camera model	FC 300-S
FOV	94 °
Camera focus	3.6mm
Sensor size	6.16mm*4.62mm
Maximum resolution	4000*3000
Effective pixels	12.4 million

Table 1. UAV and sensor parameters

3.2 Images Spatial Resolution Calculation

The calculation of UAV image resolution is an important data pre-processing task. The spatial resolution of an image refers to the size of the actual ground size which the pixels on the image are mapped, and the smaller the size, the higher the resolution (Yang RS., 2013). For UAV systems, the flying height has a great influence on the resolution of the image, and the higher the flying height, the lower the spatial resolution of the image (Fig.2). The spatial resolution of the image is also affected by camera parameters. The image resolution is calculated as follows：

$$GSD = (H \times \alpha)/f \qquad (1)$$

Where GSD=ground resolution in units of m
H=flight height in m
α= pixel size in µm
f=camera focal length in mm

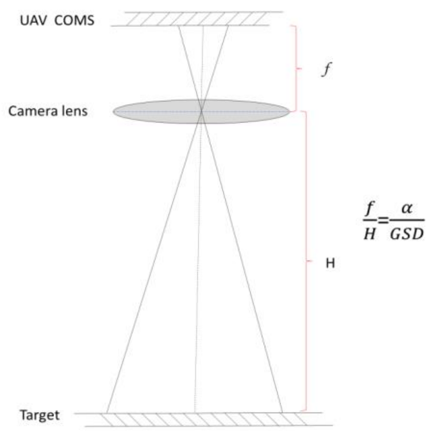

Figure 2.Image Spatial Resolution Calculation

3.3 Object-oriented Burrows Extraction

The principle of object oriented classification (Peña J.M., 2013) is to first segment images into many objects, each of which is homogeneous, and there are differences between objects and objects. Classification is based on objects, not based on a single pixel, which can greatly improve the classification accuracy and reduce the classification noise. For image segmentation, this paper is carried out under the eCognition software.

In this paper, a common multi-resolution segmentation algorithm (Rahman M.R., 2008) is used to merge images from bottom to top into many image objects based on the principle of internal homogeneity. Segmentation parameters mainly include scale, colour, shape, smoothness, and compactness. The smaller the parameter is set, the more the number of objects after the segmentation is, and the more broken the segmentation is. The larger the parameter setting, the smaller the number of objects after the segmentation, and the greater the possibility that the feature will be misclassified. In this paper, we set up different segmentation parameters (Table 2) through many experiments. By comparing the effect of segmentation (Figure 3), we finally determined the best segmentation parameters of four images.

A	Level 1	Level 2	Level 3	Level 4
Scale	30	60	100	150
Shape	0.5	0.5	0.5	0.5
Color	0.5	0.5	0.5	0.5
Compact	0.8	0.8	0.8	0.8
Smooth	0.2	0.2	0.2	0.2
Object number	32913	7882	2570	1008
B	**Level 1**	**Level 2**	**Level 3**	**Level 4**
Scale	20	30	50	100

Shape	0.5	0.5	0.5	0.5
Color	0.5	0.5	0.5	0.5
Compact	0.8	0.8	0.8	0.8
Smooth	0.2	0.2	0.2	0.2
Object number	53371	29054	10151	3685
C	Level 1	Level 2	Level 3	Level 4
Scale	20	20	30	50
Shape	0.2	0.5	0.5	0.5
Color	0.8	0.5	0.5	0.5
Compact	0.5	0.8	0.5	0.5
Smooth	0.5	0.2	0.5	0.5
Object number	68512	48025	23851	7802
D	Level 1	Level 2	Level 3	Level 4
Scale	20	20	30	50
Shape	0.2	0.5	0.5	0.5
Color	0.8	0.5	0.5	0.5
Compact	0.5	0.8	0.5	0.5
Smooth	0.5	0.2	0.5	0.5
Object number	67183	44591	25234	8603

Table 2. Multi-resolution segmentation parameters

Spectral difference segmentation strictly speaking cannot be regarded as a segmentation algorithm, it cannot create a new segmentation layer based on the pixel layer, but based on the existing segmentation layer, by analysing whether the brightness difference of the adjacent segmentation objects meets the given threshold to decide when to merge objects. Multi-resolution segmentation combined with spectral difference segmentation can merge objects with relatively similar brightness values, reduce the number of segmentation objects, and optimize the segmentation results.

Supervised classification, also known as training classification, refers to the technique of selecting training samples for classification through prior knowledge. The traditional supervised classification is based on pixel-level classification, while the supervised classification of the object-oriented method is based on the segmented objects. Object-based supervised classification can reduce the noise generated by image classification, resulting in more accurate classification results.

4. RESULTS AND ANALYSIS

4.1 Images spatial resolution calculation

The FC 300-S sensor size is 1/2.3 inch and the pixel size is 1.5 μm. According to formula (1) we calculated the spatial resolution of the four images as Table 3. In image A, we can clearly see the burrows. And the width of the burrows is about 50-60 pixels. While in image D, the burrows is only about 4-6 pixels wide.

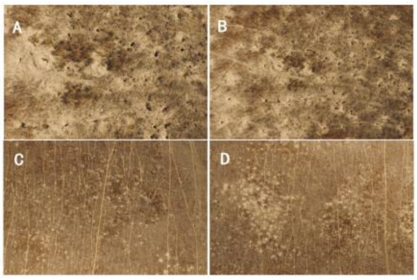

Figure 3. Different spatial resolution images

Image	A	B	C	D
H	3m	6m	24m	30m
GSD	0.125cm	0.25cm	1cm	1.25cm

Table 3. GSD calculation for four images

4.2 Images segmentation results

Comparing the multi-resolution segmentation results of local regions, we found that the Level 1 segmentation scale was insufficient and the map spot is too fragmented on the A image. In the Level 2 segmentation scale, although the burrows segmentation effect was ideal, the large bare land and the grassland were fragmented too much. At the Level 4 scale, burrows were not well segmented. Therefore, Level 3 was selected as the optimal segmentation layer (the effect of mouse hole segmentation can be seen in the red range). Similarly, compared with the other three images, the optimal segmentation layers are: B: Level 3, C: Level 3, and D: Level 2.

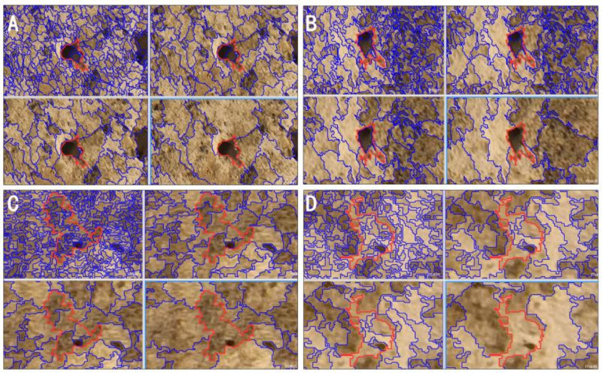

Figure 4. Multi-resolution segmentation results

4.3 Burrow extraction and accuracy assessment.

According to the classification results of UAV images, we found that burrows were clearly visible on aerial images. From the results of the extraction, there are some errors in the burrows classification results. The dark shades of some vegetation and the clefts on the ground became clearer, which lead that the computer interpreting has a wrong identification. At the same time, some of the bare land samples were classified into grasslands. This may be due to the aerial time of autumn, when the grass was withered and yellow, and there were traces of disturbance in the bare land. These caused the bare reflectance spectrum characteristics to be very similar to that of the yellow forage.

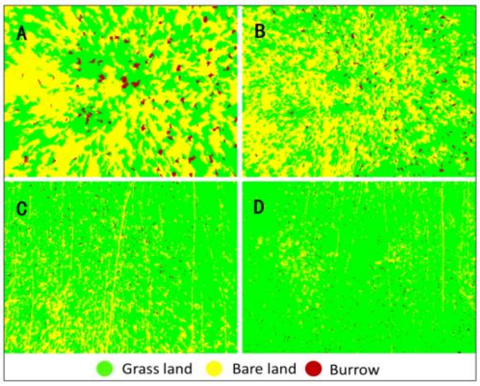

Figure 5. Burrow classification results

A	Burrow	Grassland
Burrow	15	11
Grassland	0	79
Bare-land	0	10
Sum	15	100
B	Burrow	Grassland
Burrow	25	6
Grassland	5	80
Bare-land	0	14
Sum	30	100
C	Burrow	Grassland
Burrow	52	7
Grassland	6	187
Bare-land	2	6
Sum	60	200
D	Burrow	Grassland
Burrow	84	19
Grassland	16	180
Bare-land	0	1
Sum	100	200

Table 4. Sample confusion matrix

Image	A	B	C	D
Overall accuracy	75.3%	78.7%	92.8%	85.8%
KIA	0.578	0.649	0.881	0.778

Table 5. Classification accuracy verification

In order to evaluate the accuracy of the classification results, we randomly selected a certain number of samples on the four images by visual interpretation and evaluated the classification results. According to the accuracy evaluation confusion matrix (Tab.4&5), we found that:

(1) Burrow samples were well classified when the flying height was 3m (GSD, 0.125cm). 11% of grassland samples were classified as burrows because grass shadows and burrows are more difficult to distinguish. While, there were 31% of bare samples have been classified as grassland.

(2) When the flying height of 6m (GSD, 0.25cm), the classification accuracy of burrow reached 83.3%, while some grassland samples were misclassified into burrow and bare land, and 24% of bare land samples were misclassified into grassland.

(3) When the flying height is of 24m (GSD, 1cm), the classification accuracy of burrow reached 86.7%, and the classification accuracy of grassland and bare land has increased to more than 90%, which lead the improvement of the overall classification accuracy (92.8%).

(4) When the flying height is of 30m (GSD, 1.25cm), the classification accuracy of the burrow was 84%, the grassland classification accuracy was 90%, and the bare land classification accuracy was 82.5%.

From Tab.5, we found that the classification accuracy of burrow is the best, with an average of more than 80%. With the reduction of spatial resolution, the classification accuracy of grassland has also been improved, and the discrimination between bare land and grassland has become more pronounced. At a flying height of 24 m and a spatial resolution of 1 cm, the classification accuracy of the object is the highest (Overall Accuracy 92.8%, KIA 0.88).

5. CONCLUSIONS AND DISCUSSION

In this paper, Ba Yin Gou pasture was selected as research area and DJI PHANTOM-3 as remote sensing platform. We used four different flying heights (3m, 6m, 24m, and 30m) to shoot the rat holes and calculated the spatial resolution of the images corresponding to the four altitudes. We used the object-oriented supervised classification method to extract the four mouse holes. And based on the random samples, the accuracy of the classification results was evaluated. We the conclusion that when the altitude is 24m, the image spatial resolution is 1cm, the extraction accuracy of burrow is the highest.

With the increase of altitude and the decrease of spatial resolution of images, the classification accuracy of grassland and bare land has also been improved，which may be due to the excessive spatial resolution that can amplify the detailed features of the features. This will cause some confusion in the image classification, thus reducing the classification accuracy. Obviously, under certain circumstances, blind pursuit of excessively high spatial resolution may not necessarily lead to an increase in the classification accuracy, but it also inevitably results in a problem of excessive data volume.

The burrows recognition accuracy is about 80%，it because that the spectral reflection characteristics of dark vegetation shadow and the rat hole are relatively close. In the future, the spectral characteristics features will be considered to improve the rat hole recognition accuracy.

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