APPLYING UNMANNED AERIAL VEHICLE IMAGES TO INTERPRET MIXTURE FRUIT TREES IN MOUNTAIN AREAS

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ABSTRACT

Interpreting the crop areas of farmland in Taiwan using remote-sensing technology is particularly difficult, because a variety of crops are planted in a small area, resulting in fragmented and complex farmland patches. The very high-spatial-resolution imagery of unmanned aerial vehicle (UAV) images can be utilized to overcome these difficulties. This study used aerial images taken using UAVs for land cover classification of a study area in Gongguan Township, Miaoli County, followed by the use of image segmentation. The segmentation blocks generated and cadastral maps were combined to perform manual interpretation.

The interpretation results indicated that the classification results that underwent multiresolution segmentation were highly effective, with an overall accuracy of 91.6% and a Kappa value reaching approximately 0.9. Due to the low flight altitude, the spatial resolution can be exceedingly high, enabling accurate interpretation of land cover. The results of this study indicate that UAVs are suitable for land cover surveys in small, specific areas.

1. INTRODUCTION

Remote-sensing technologies and platforms have been under development, particularly in agricultural research, which has shown a trend of gradual growth (Nam et al., 2015; Na et al., 2012; Lee et al., 2011). Interpreting the crop areas of farmland in Taiwan using remote-sensing technology is particularly difficult, because Taiwan's agriculture is intensive. A variety of crops are planted in a small area, resulting in fragmented and complex farmland patches. Even several hybrid varieties of fruit trees in mountainous areas may appear in the same farmland patch. These situations render it challenging to make distinctions when using images for interpretation; frequently, high-spatial-resolution images such as WorldView-3 and Geo-eye images must be used. However, these images are expensive, and high-quality images are often difficult to obtain due to cloud cover. Therefore, it is necessary to obtain images with low costs and high mobility that are not easily affected by cloud cover, such as unmanned aerial vehicle (UAV) images.

Agricultural research using UAV technology has examined vegetation classification (Senthilnath et al., 2017), weed mapping (Gómez-Candón et al., 2014), and crop interpretation (Bendig et al., 2015). The limitations of traditional aerial photography can be resolved through the low-altitude remote sensing (LARS) of UAVs (Huang et al., 2013), and the accuracy of subdividing species can be enhanced by the very high-spatial-resolution imagery of UAV images (Lu and He, 2017), as a reference for other future applications.

Several studies have suggested that in the classification and interpretation of land cover samples, object-based image analysis (OBIA) is more advantageous than pixel-based image classification (Diaz-Varela et al., 2014), as well as more accurate (Laliberte et al., 2010). OBIA can solve certain disadvantages of pixel-based image classification, such as reducing the possibility of the "salt-and-pepper" effect (Dronova et al., 2012). Particularly in very high-spatial-resolution imagery such as UAV images (Blaschke, 2010; Drăgut et al., 2010), OBIA can significantly increase accuracy (Feng et al., 2015). Therefore, current studies of UAV images in agricultural applications use OBIA to assist interpretations. The present study also utilized OBIA methods, using the multiresolution segmentation in eCognition to perform image segmentation, and then using the blocks after image segmentation for interpretation.

The continuing development of UAV remote-sensing technology has influenced each field to varying degrees, and demonstrated immense potential. This study used aerial images taken using UAVs for land cover classification of a study area in Gongguan Township, Miaoli County, followed by the use of image segmentation. The segmentation blocks and cadastral maps were combined to perform classification. However, because layered planting was used to plant both betel nuts and persimmons at the higher and lower levels in the study area, sample selection for an automatic interpretation was difficult. This study thus employed manual interpretation to provide a land mapping method that increases the accuracy of classification.

2. MATERIALS AND METHODS

2.1 Study area

This study was conducted in Gongguan Township, Miaoli County, in a surveyed area of approximately 500 ha (see Figure 1). Although this area was primarily level ground, a mountainous region was located in the southeast, with the Houlong River as the boundary between the two regions. In the level ground region, rice paddies, taro, red dates, and grassland were primarily planted. The mountainous region had a cover composed of persimmons, betel nuts, and woodland. This area had a subtropical monsoon climate with a mean annual temperature of 21 °C, mean annual rainfall of 1600 mm, and an average humidity of approximately 80%, rendering it suitable for crop growth.

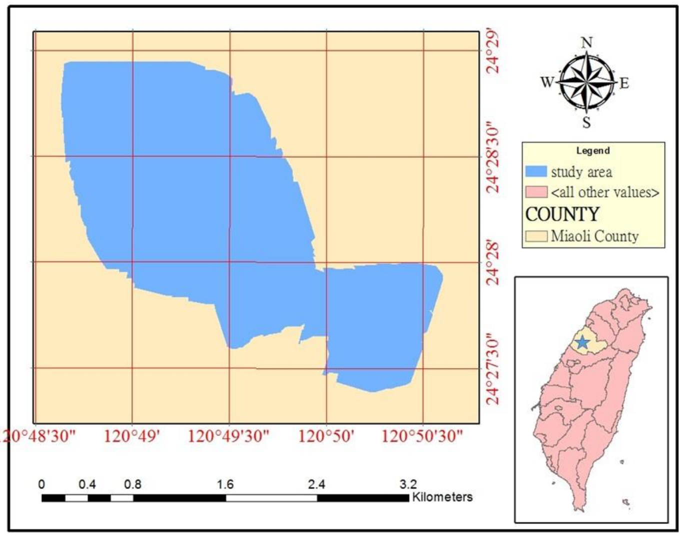

Figure 1. Study area

2.2 Image Collection

A fixed-wing UAV was used for aerial photography. The UAV model used was the senseFly eBee, with an approximate weight of 0.69 kg and a wing span of 96 cm. The UAV was composed of EPP foam, a carbon structure, and composite parts; its power was derived from an electric pusher propeller and a 160 W brushless DC motor, and the maximum flight duration was 50 min. The eMotion 2 was employed to perform flight control and route planning. This fixed-wing UAV did not require catapults or additional components; the UAV only had to be shaken three times to start the motor and then thrown into the air to begin flight, and could be used for flight missions in locations without open runways.

This study obtained an airspace license from the Civil Aeronautics Administration (MOTC) and performed nine flights between April 6 and 7, 2017. The flight time was 134 min 28 s, and a Canon Ixus 127 camera was used to obtain RGB images with an average resolution of approximately 4.53 cm. A Canon S110 NIR camera was also used to obtain multispectral images with an average resolution of approximately 18.67 cm. The obtained bands were comprised of B, G, R, red edge, and near-infrared. The aerial photography was followed by image stitching using Agisoft PhotoScan Professional to construct complete aerial images of the study area (as shown in Figure. 2).

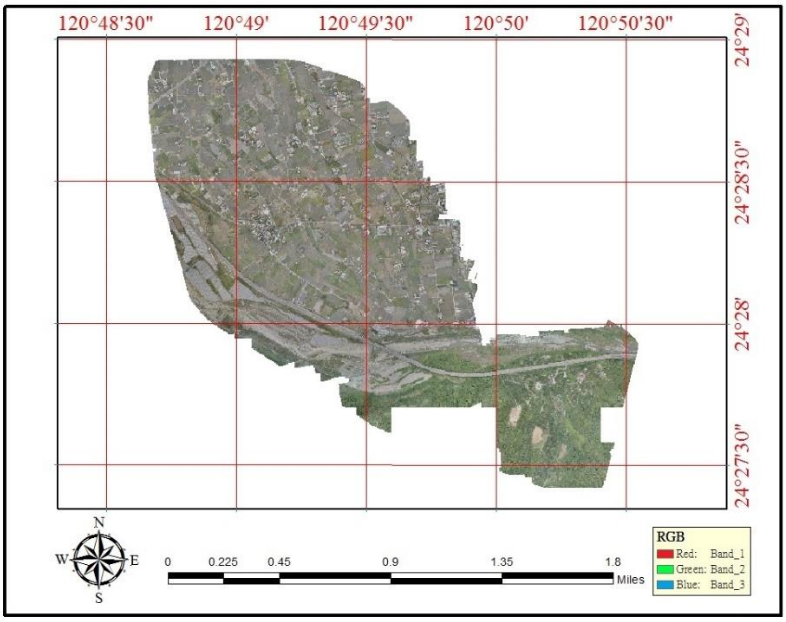

Figure 2. UAV images

2.3 Field Survey

The ground survey conducted by this study was based on a cadastral map (Figure 3), followed by the collection of actual planting data. The data was recorded on the cadastral map, then on-site photos were obtained, and a geographic information system was employed to form this data into ground-truth data.

The cover of the study area was primarily composed of woodland, persimmons, betel nuts, rice paddies, red dates, taro, grassland, bare land, buildings, and bodies of water. A small portion of other crops were also present; because these crops were overly scarce, data on these crops were combined into the category of “Other” in ground-truth data. This category was comprised of 12 sub-categories, including corn, dragonfruit, cabbage, and crops on net racks.

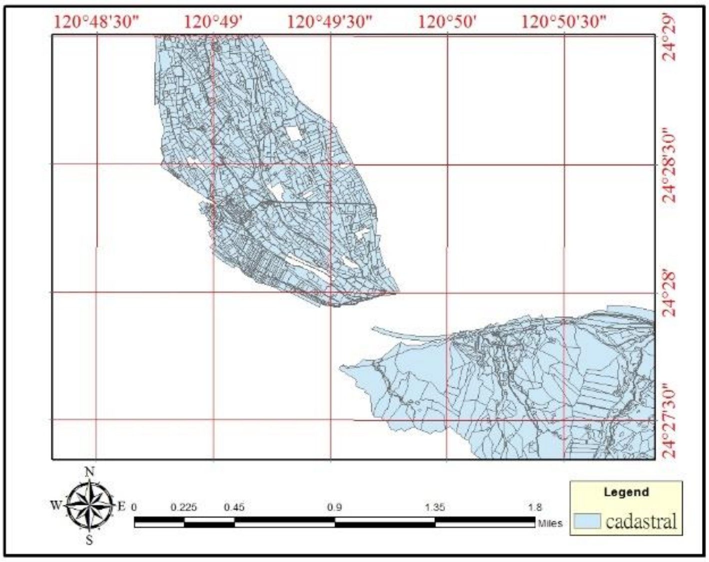

Figure 3. The cadastral map

2.4 Image Interpretation

After the aerial photography was completed and the ground-truth data obtained, image segmentation using eCognition was first performed on aerial images. After the segmentation was completed, ground-truth data was used to perform an inspection to ensure that the blocks were composed of single species after image segmentation, and not overly fragmented. After the image segmentation passed inspection, manual interpretation methods were employed to interpret the cover crops on the entire aerial image, on the basis of a cadastral map and segmentation block diagram. The classification process was divided into single-species and multi-species patches. For a patch interpreted as single-species, the interpreted species was directly recorded onto the cadastral map. However, for a patch interpreted as multi-species, it was necessary to record these species onto the segmentation blocks. Therefore, the classification results included the data of the cadastral map and segmentation blocks. Once classification of the entire image was completed, the cadastral map and segmentation block diagram were merged into a single classification results image.

3. RESULTS AND DISCUSSIONS

3.1 Segmentation

The segmentation block diagram generated using the multiresolution segmentation of eCognition is shown in Figure 4. When the segmentation scale was 250, the heterogeneity of each single block was low, resulting in the maximization of blocks. After image segmentation, the patches were finer than those in the original cadastral map, yet not overly fragmented. If the original cadastral map was used, patches with more than two types of crops required segmentation. However, segmentation became complex when different crops were mixed and planted together; thus, using eCognition could increase the efficiency of interpretation.

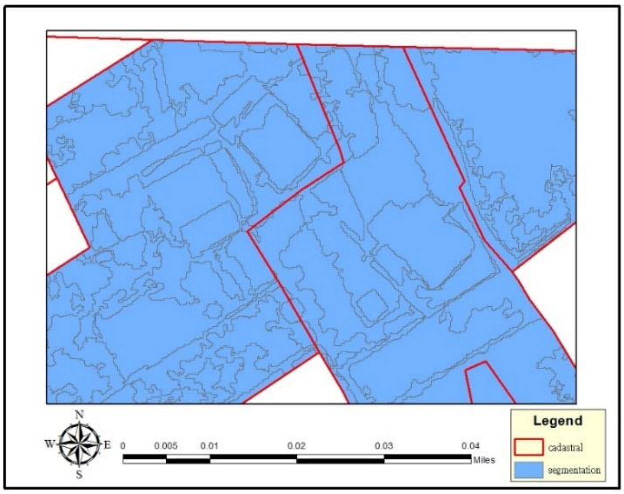

Figure 4. Examples of segmentation block diagrams

3.2 Accuracy Assessment

The interpretation results (Figure 5) indicated that the classification results that underwent multiresolution segmentation were highly effective, with an overall accuracy of 91.6% and a Kappa value reaching approximately 0.9 (Table 1). In the study, categories with a larger cover area (rice paddies, red dates, taro, and woodland) accounted for higher than 80% of the overall area. The classification accuracy was higher than 88% for all of these categories, whereas the categories whose accuracy was less than 88% accounted for only approximately 11% of the overall area.

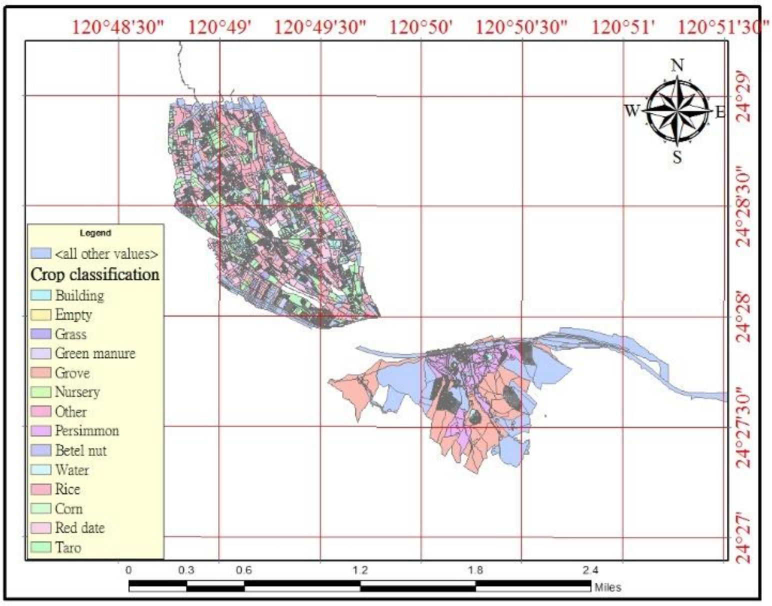

Figure 5. Interpretation results

For many fields on level ground, only the patches in the cadastral map were required for interpretation because most fields on level ground were complete patches. Segmentation block diagrams were only required for the classification of red dates, for which several portions of the field were unplanted land, and for buildings or areas around lakes, where woods were planted or portions of the field were non-vegetated areas, because the land types of these fields were more fragmented and complicated.

Table 1. Classification Accuracy

	Producer's Acc.	User's Acc.	Overall Acc.
Buildings	93.4	95.9	91.6
Bare land	59.8	62.6	KAPPA
Grassland	68.9	83.6	0.9
Woodland	97.6	98	
Plant nursery	80.7	98.7	
Other	87.9	72.5	
Water	100	93.1	
Persimmons	96.8	94.7	
Betel nuts	98.5	99.7	
Rice paddies	94.6	91	
Red dates	93.8	89.5	
Taro	88	94.5	

From the results, it is evident that the classification results for betel nut plants were the most favorable. Both the producer's accuracy and user's accuracy were higher than 98%. The betel nut plant is clearly distinguishable; thus, provided that the spatial resolution of the image is sufficient, the betel nut plant is readily interpreted (as shown in Figure 6). Following betel nuts were the results for woodland, which also obtained accuracies higher than 97%. In addition, persimmon trees were easy to distinguish because the fruit trees in that part of the study area comprised only one type, and the spectral distributions of persimmon trees were distinct from those of regular woods. Persimmons also only cross-breed with betel nuts; therefore, the classification results for both the woodland and persimmons were favorable, and the accuracy of persimmons was also higher than 94%. However, a few persimmon trees and woodland were mistaken, mostly in the boundaries between persimmons and woodland.

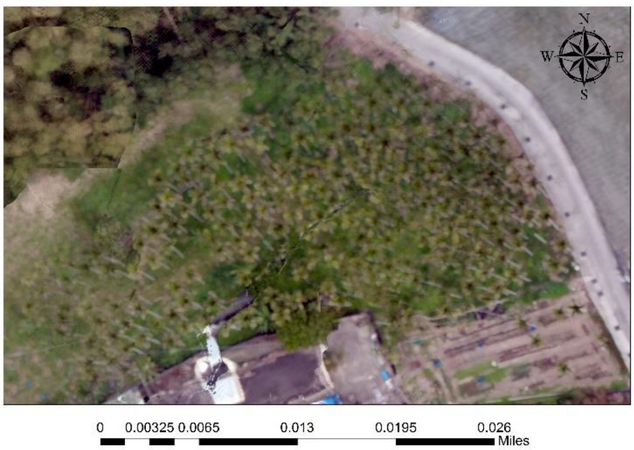

Figure 6. Betel nuts

The spectral distributions of buildings and water were distinct from those of other categories, and the producer's and user's accuracies of these two categories were higher than 93%. Although both rice paddies and taro possess distinguishing characteristics, the two species were easily mistaken for one another because both are grown in paddy fields, and are thus easily mistaken during their growth stages (as shown in Figure 7). During aerial photography, several red date plants were still in early stages of growth. The reactions of red date plants in this stage are not evident (as shown in Figure 8); if the land is overgrown with weeds, these plants are easy to confuse with grassland. Moreover, if weeds are absent and the land appears empty, an area with young red date plants can easily be confused with bare land.

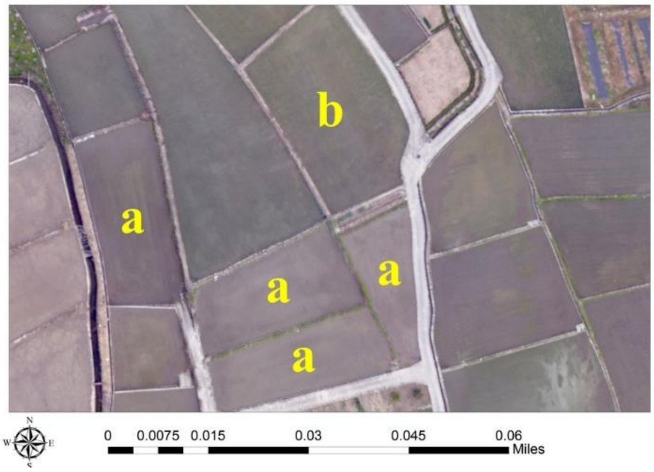

Figure7. (a) Rice paddies and (b) taro

Figure8. Red dates in early stages of growth are easy to confuse with grassland.

Bare land and grassland, which had the least favorable classification results of this study, were easy to confuse with one another and with red dates. However, because the planted area of red dates was so large, the accuracy of the results for red dates was correspondingly high. By contrast, grassland and bare land, which occupied less area, had less favorable interpretation effects.

4. CONCLUSIONS AND SUGGESTIONS

This study applied OBIA to the classification and interpretation of UAV images. The mobility and resolution of UAVs are higher in comparison to those of satellites and airplanes, and images can be obtained during cloud cover; however, problems persist: the flight times of UAVs are insufficient, their camera ranges are small, and the manual interpretation requires a long period of time.

The results of this study indicate that UAVs are suitable for land cover surveys in small, specific areas. Due to the low flight altitude, the spatial resolution can be exceedingly high, enabling accurate interpretation of land cover. As a result, the overall accuracy of this study reached 91%. However, although the interpretation of small areas using UAVs is effective, for surveys of large areas, substantially more time is required for obtaining images. More time required for interpretation also increases costs as well, and cost-effectiveness must be considered.

The results also indicate that the interpretation accuracies for woodland, betel nuts, and persimmons were all high, proving that the OBIA could be used in the interpretation of tree species and of hybrid zones. However, crops planted in higher and lower levels still cannot be effectively managed; for instance, in a mountainous area of the study area where persimmons were planted, layered planting was used to plant persimmons together with betel nuts in some patches (as shown in Figure 9). The researchers were unable to solve this problem during this study. During classification, the patches were interpreted as persimmons, and during on-site surveys they were also recorded as persimmons. Therefore, the data did not reflect this situation, and at present it cannot be effectively overcome.

Figure 9. Layered planting of betel nuts and persimmons

This study showed that performing image segmentation for aerial photography, followed by on-site surveys using a segmentation block diagram as a basis, would lead to more favorable results than on-site surveys based on cadastral maps. Ground-truth data generated by the segmentation block diagram could more accurately represent land cover locations and ranges. For instance, for the red dates in this study, gaps were left between each plant during planting. The gaps were either bare ground areas (as shown in Figure 10) or weeds, and image segmentation divided red dates and portions of bare land or weeds into different blocks. If the ground-truth data was drawn based on a cadastral map, and the area was recorded as red dates in the on-site survey, the range of the entire patch will be identified as red dates in the ground-truth data. This leads to the misinterpretation of red dates as bare land or grassland, resulting in decreased accuracy. Therefore, it is more accurate to use ground-truth data generated from a segmentation block diagram to perform comparisons.

Figure 10. Red date planting gaps.

For areas in Taiwan where farmland patches are fragmented and complicated and often hybrid, this study recommends that UAV images be used to assist aerial photography or satellite imagery when performing large-scale land cover surveys. First, a few small-scale sample areas can be selected using UAV aerial photography to obtain images of the sample areas. Subsequently, OBIA can be used for the UAV images. Using the generated segmentation block diagram as a basis, a field survey can be conducted to obtain more accurate ground-truth data, which can then be used to perform large-scale land cover classification of aerial or satellite images to achieve more favorable results.

5. FUNDING

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