APPLICABLE MEAN-SHIFT FILTERING PARAMETERS FOR MAPPING OF WEED IN CASSAVA FIELDS BASED ON UAV IMAGES

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ABSTRACT: Recently, a very high spatial resolution image for precision agriculture can be collected from sensors mounted on the Unmanned Arial Vehicle (UAV), which is less time-consuming, has accurate control, high performance, and low operation cost. As the high spatial resolution, the object in this image contains many pixels that vary differently in the pixel value. Image classification results of using raw pixel values may be affected by the heterogeneous properties of objects. Mean-shift filtering is a process to smooth the different fine pixels into the homogeneous region and remove noise from plenty of small areas on the image. The appropriate parameters are crucial to filter this process. This study explores the applicable mean-shift filtering parameters, spatial size, and color value to improve the classification accuracy of weeds and cassavas. The RGB image from the UAV was used as an input dataset for the mean-shift process. Consequently, the filtered images were classified by the Support Vector Machine (SVM), presenting the weeds and cassavas map. The experimental result shows that using Mean-shift filtering can increase classification accuracy up to 4.22% from pixel-based classification by varying different sets of parameters. The classification accuracies are 78.38% - 82.60%. It shows that the mean-shift filtering with the appropriate parameters can be employed to improve the classification accuracy.

1. INTRODUCTION

Weed detection is necessary for the weed management process by using an automatic machine or herbicide. A very high spatial resolution image for weed detection can be collected from sensors mounted on the UAV, which is less time-consuming to obtain the image and low operation cost. The very high-resolution image contains many pixels that can differ the characteristic of even a single object. The heterogeneity in an object causes the different results of the segmentation and classification process (Huang, Li, & Chen, 2018). Using the appropriate filter to reduce the heterogeneity of an object can produce smoother image pixels, form clearer clusters, and remove noises in the image. For this reason, many researchers (e.g., Davies, 2018; Georgescu, Shimshoni, & Meer, 2003; Tao, Jin, & Zhang, 2007; Zhou, Wang, & Schaefer, 2011) considered a mean-shift technique to improve the accuracy of the classification results.

This study examined the appropriate mean-shift parameters to filter weeds and cassavas in the cassava field on high-resolution images from the UAV. The RGB high-resolution images were used to investigate the mean-shift filtering process. The mean-shift filtering was utilized for preprocessing to enhance the input data for the classification process (Yang, Rahardja, & Fränti, 2021). The filtered images were classified by Support Vector Machine (SVM) technic to present weeds and cassavas classified maps.

2. MATERIAL AND METHODS

2.1 Study Area and Dataset

The experimental image is in Figure 1. The Cassava field is located in Mueang district, Nakhon Ratchasima province, Thailand. A DJI Phantom 4 Pro quadcopter was used to take high-resolution images over the experimental area (in the red box of Figure 1) on April 28th, 2018. A built-in optical sensor in a UAV camera provides twenty million pixels with a CMOS sensor, 8.8 mm/24 mm (35 mm format equivalent). The lens with a field of view (FOV) of 84° and a three-axis stabilization gimbal is mounted on the UAV for this study. The flight altitude was 40 meters above the ground level with 80 % of both side-lap and overlap. The UAV images were processed and mosaiced by Pix4Dmapper software. The spatial resolution of the mosaic image was resampled to 2.5 cm with values from 0 to 255 on each red, green, and blue layer.

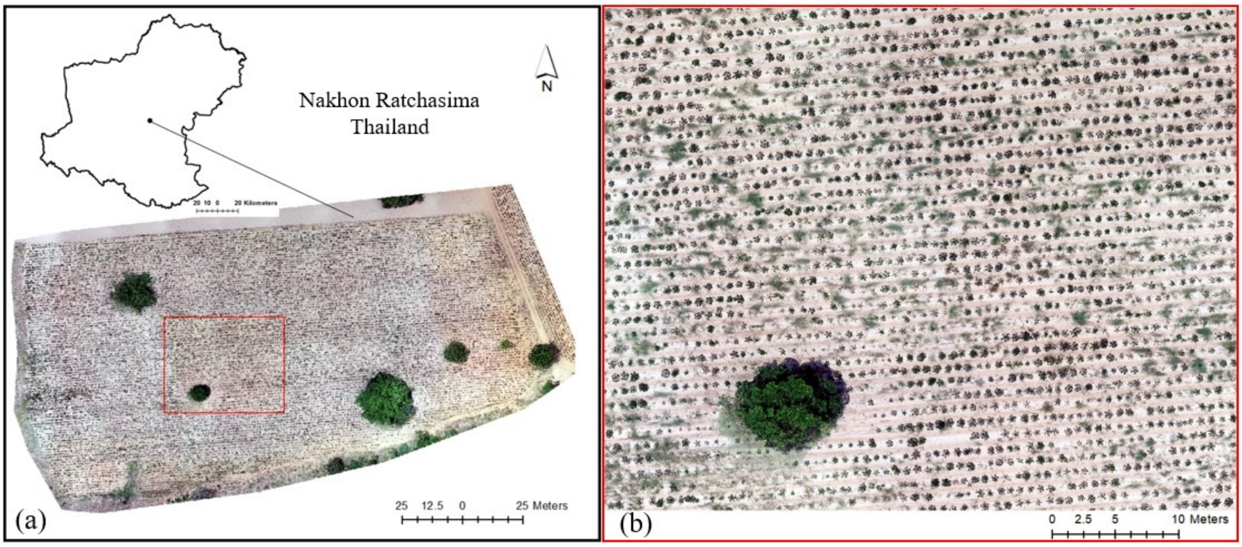

Figure 1 Cassava field (a) and Overview of experimental image (b).

The experimental image size, 40 x 50 meters, consists of cassavas, weeds, soil, and trees. The study area represents the characteristic of the cassava plantation. The four-month cassavas were infested with weeds, and the perennial trees cover part of cassava and weed in the field (Figure 2a-b). The samples of classes (Figure 2c) were collected by visual interpretation from the experimental image for the classification processes. The varieties of spectral values extracted from the high-resolution RGB image were plotted, the boxplot presented a wide range of spectral values and the overlapping between classes (Figure 2d). The values of the class were derived from average pixel values within the sample polygons to train the classification model. The classification model will learn from 200 data of cassava polygons, 200 data of weed polygons, 200 data of soil polygons, and 40 data of tree polygons.

For assessment of the classification quality, a total of 592 points were selected by visual interpretation from the UAV image before the classification process. The validation checked points consist of 110 points from cassava, 116 points from weed, 337 points from the soil, and 29 points from the tree. The training and validation for each type of class were randomly selected and distributed in the study area.

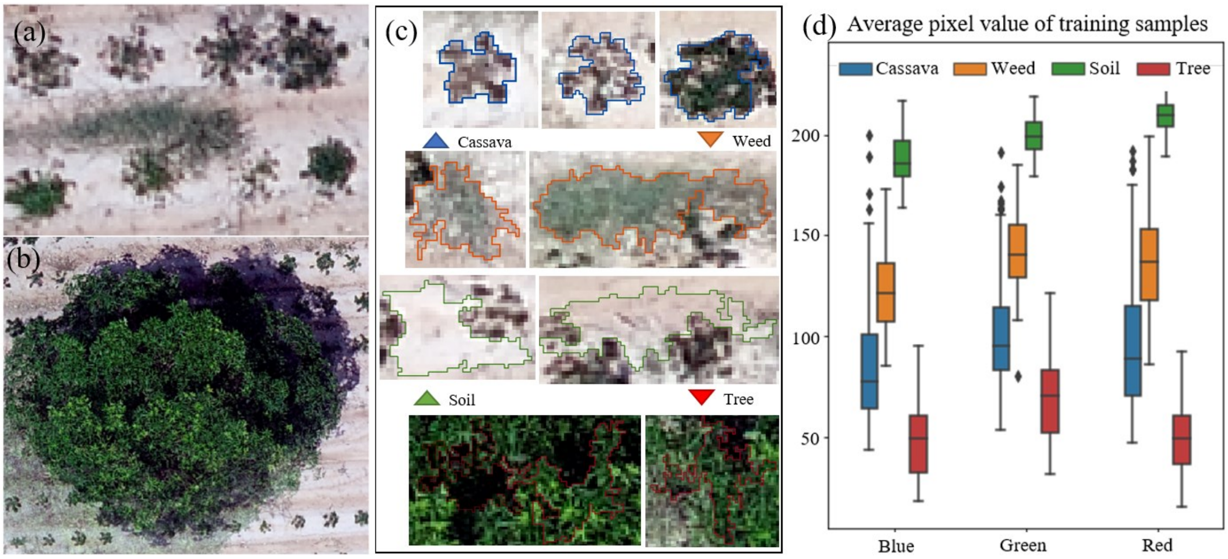

Figure 2 The characteristic of the experimental image: enlarged image for cassavas, weeds, soil, and tree (a)-(b), the samples of classes (c), and spectral value of samples (d).

2.2 Methods

The RGB image was filtered using the mean-shift algorithm, then classified by Support vector machines (SVM) technic. The image was classified into four classes, 1) cassava, 2) weed, 3) soil, and 4) tree. The classification result was assessed by using a confusion matrix. The flowchart of this study is presented in Figure 3.

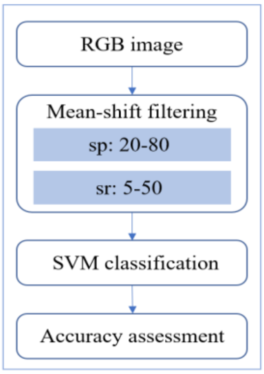

Figure 3 Flowchart of the process of this study.

Mean shift filtering: Mean shift is a non-parametric feature space analysis technique for clustering analysis. The mean-shift method considers both geometric and photometric of the image during the process (Song, Gu, Cao, & Viberg, 2006). This method can examine a cluster by replacing the target pixel with the mean value of its neighboring values in the window. The mean-shift is only controlled by the kernel size (bandwidth) and requires less manual intervention than other algorithms (Zhou, Wang, & Schaefer, 2011). As recommended by Song et al. (2006), selecting the fitting bandwidth parameters is crucial because it can enhance the image to get the best result in the classification process. The mean-shift filtering function requires the window size for spatial (sp) and color (sr) neighbors. Considering this experiment, the sp and sr varied from 20-80 for the increment of 20 units and 5-50 for the increment of 5 units, respectively, to examine the best classification accuracy.

Support vector machine Classification: The support vector machines (SVM) method is a supervised classification that can perform highly accurate and robust used widely for weed detection (Ishak, Mustafa, Tahir, & Hussain, 2008; Karimi, Prasher, Patel, & Kim, 2006; Pulido, Solaque, & Velasco, 2017). The objective of SVM is to find the most actual boundary or hyperplane to discriminate the classes, where the data close to the classification margin calls support vectors. The SVM classifier performance is controlled by kernel type, Gaussian kernel or gamma (G), and bias-variance trade-off (c). The kernel function uses the relation of the types of the dataset: linear or non-linear. For the non-linear kernel, the shape of the kernel function is controlled by G. The small G results in high constrained SVM model and cannot capture the complexity of the data. Then the model will behave similarly to a linear model. The higher the gamma, the more influence the features will have on the decision boundary. For both linear and non-linear functions, the tuning parameter c controls the soft or hard margin for separating classes. Soft margin allows more support vectors that are low bias but high variance. In contrast, if c is large (hard margin), there will be fewer support vectors, and hence the resulting classifier will have high bias but low variance. The Kernel function finds the hyperplane by inputting data into the higher dimensional space, which helps classify the data.

In this experiment, the SVM model was generated individually for each input image to assess the optimal classification parameters. The kernel types were selected from linear or radial basis functions. The parameters G and c were chosen from the range 0.0001-1 and 0.1-1000. The spectral value of original RGB images and RGB filtered images were used as input data for modeling. The highest accuracy model was applied for the classification process. The accuracy and precision in each class were presented by Kappa coefficients and confusion matrix showing the performance of the classification models.

3. Results

3.1 Image Filtering

In this study, there were 40 different conditions of mean-shift parameters for the filtering process. After applying the mean-shift filtering, the RGB images present the results, as shown in Figure 4. The spatial window sizes in the range of 40-80 show similar results. The larger color window offers a higher smoothness. However, over smoothness will remove some vital image details.

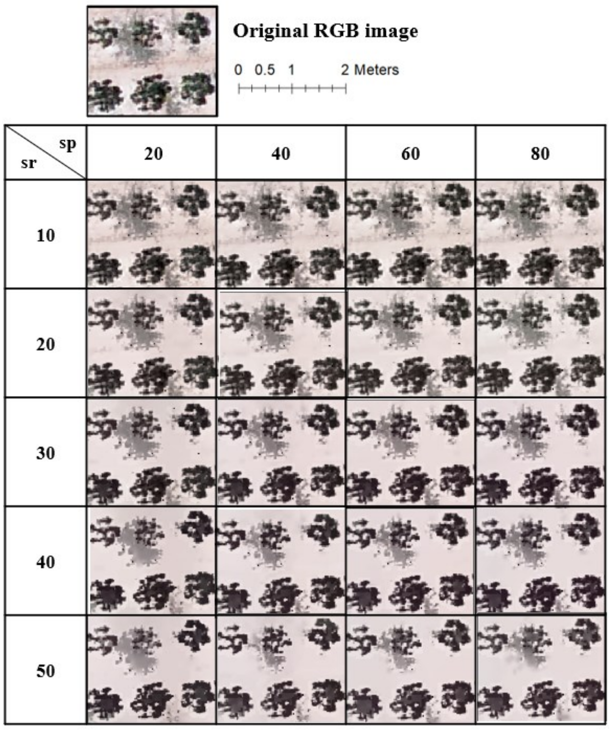

Figure 4 Result of different mean-shift filtering parameters with original RGB image (unfiltered).

3.2 Classification

The filtered images were classified by the SVM algorithm and accessed accuracies by the validation points. The RGB pixel-based classification was done without the mean-shift filtering for comparison.

All class accuracy: The classification accuracies and kappa coefficients of varying mean-shift parameters were plotted as a heatmap (Figure 5). The dark green color represents a high accuracy, while the light gray color represents a low accuracy. According to the heatmap, the result shows different sets of parameters with different accuracies. The overall classification accuracies are between 0.7838 - 0.8260, and the kappa coefficients are between 0.6463 - 0.7073. The highest classification accuracy presents the overall accuracy (OA) as 0.8260 and kappa coefficient as 0.7073 by setting the spatial window radius (sp) as 20 and the color window radius (sr) as 30, after applying the mean-shift filtering. Without the mean-shift filtering, the classification result presents an accuracy and kappa coefficient of 0.7838 and 0.6454, respectively. The confusion matrix of both unfiltered and filtered images with mean shift fitting parameters shows in Table 1 and Table 2. The producer’s accuracy (PA) and user’s accuracy (UA) of the soil-class image are higher than 90%. However, the PA and OA of the vegetation-class image are lower than the soil one. However, the misclassified pixels of vegetation that occurred according to the spectral were similar and perhaps mixed with other vegetation classes.

The precision of each class: The input image combines various sizes of objects so that filtering size affects the precision of each class (Figure 6). The highest precision of each class is shown in Table 3. The best precision of cassava class with the mean-shift filtering of sp was 20, and sr was 40, which reached 0.9194 of the precision value. The weed class with the mean-shift filtering shows moderate precision of 0.6557 by setting sp as 40 and sr as 45. Both soil and tree classes offer a high precision value, 0.95, as the sp was 80 and sr was 15 and 1.00 as sp was 60 and sr was 30 for the soil and tree class, respectively. It clearly shows that the filtered images present a better precision value than the unfiltered image. The classification maps of these mean shift parameters are shown in Figure 7. The small pixels in an original RGB image were almost eliminated by the mean shift filtering process, which increased the accuracy of the classification results. The sp value influenced the object’s size, in which the tree class showed a higher value than the cassava and weed class. However, the sp value of the soil class did not respond to the object’s size because the soil contained its specific size. The precision values of the soil class were slightly different (0.94-0.95) for all sp values according to the low value of sr showed much noise, in which the small pixels were similar to the unfiltered input image.

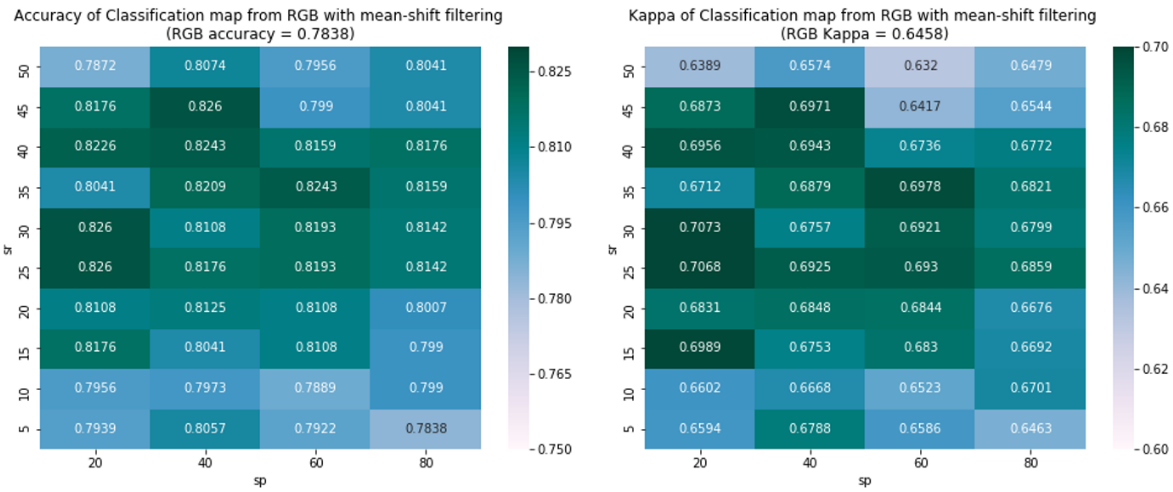

Figure 5 Heatmap of classification accuracy and kappa coefficient form difference mean shift parameters.

Table 1 The confusion matrix shows the classification of the un-filtered RGB image.

Class	**Reference**				User's accuracy (UA)
	Cassava	**Weed**	**Soil**	**Tree**	
Cassava	53	4	0	15	0.7361
Weed	49	99	36	2	0.5323
Soil	3	13	300	0	0.9494
Tree	5	0	1	12	0.6667
Producer's accuracy (PA)	0.4818	0.8534	0.8902	0.4138	
Overall accuracy (OA)	0.7838				
Kappa	0.6458				

Table 2 The confusion matrix shows the classification of RGB filtered with the best mean-shift parameter.

Class	**Reference**				User's accuracy (UA)
	Cassava	**Weed**	**Soil**	**Tree**	
Cassava	63	4	0	7	0.5814
Weed	34	92	23	1	0.6133
Soil	11	20	313	0	0.9099
Tree	2	0	1	21	0.8750
Producer's accuracy (PA)	0.5727	0.7931	0.9288	0.7241	
Overall accuracy (OA)	0.8260				
Kappa	0.7073				

Table 3 The highest precision of each class.

	Unfiltered image	**Filtered image with Mean-shift filtering**				
		sp20 sr30 (Figure 7b)	sp20 sr40 (Figure 7c)	sp40 sr45 (Figure 7d)	sp80 sr15 (Figure 7e)	sp60 sr30 (Figure 7f)
Overall accuracy	0.7838	0.8260	0.8226	0.8260	0.7990	0.8193
Kappa	0.6458	0.7073	0.6956	0.6971	0.6692	0.6921
Cassava precision	0.7361	0.8514	0.9194	0.8551	0.7761	0.7763
Weed precision	0.5323	0.6133	0.6241	0.6557	0.5372	0.6056
Soil precision	0.9494	0.9099	0.8760	0.8670	0.9500	0.9040
Tree precision	0.6667	0.8750	0.9231	0.9600	0.9412	1.000

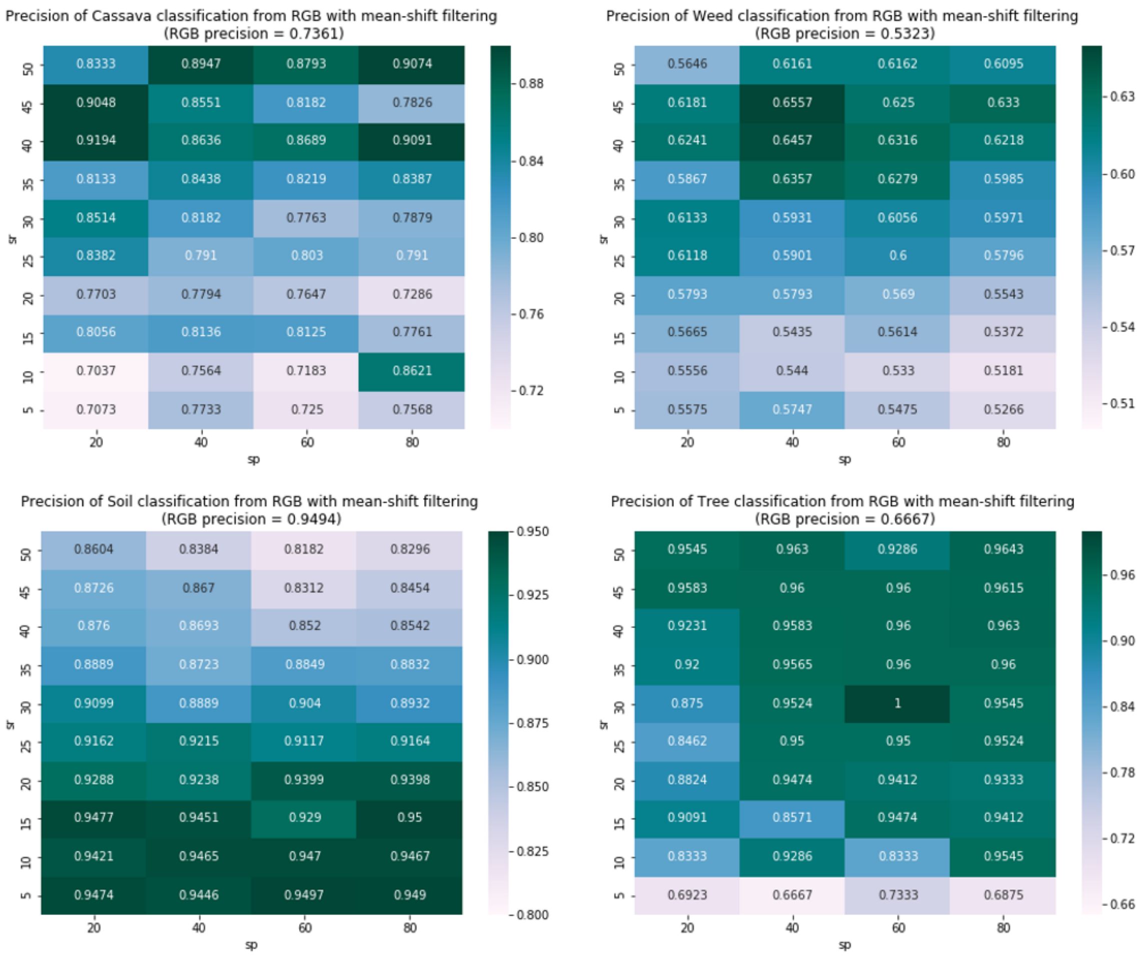

Figure 6 Heatmap of the precision of classes: cassava, weed, soil, and tree form difference mean shift parameters.

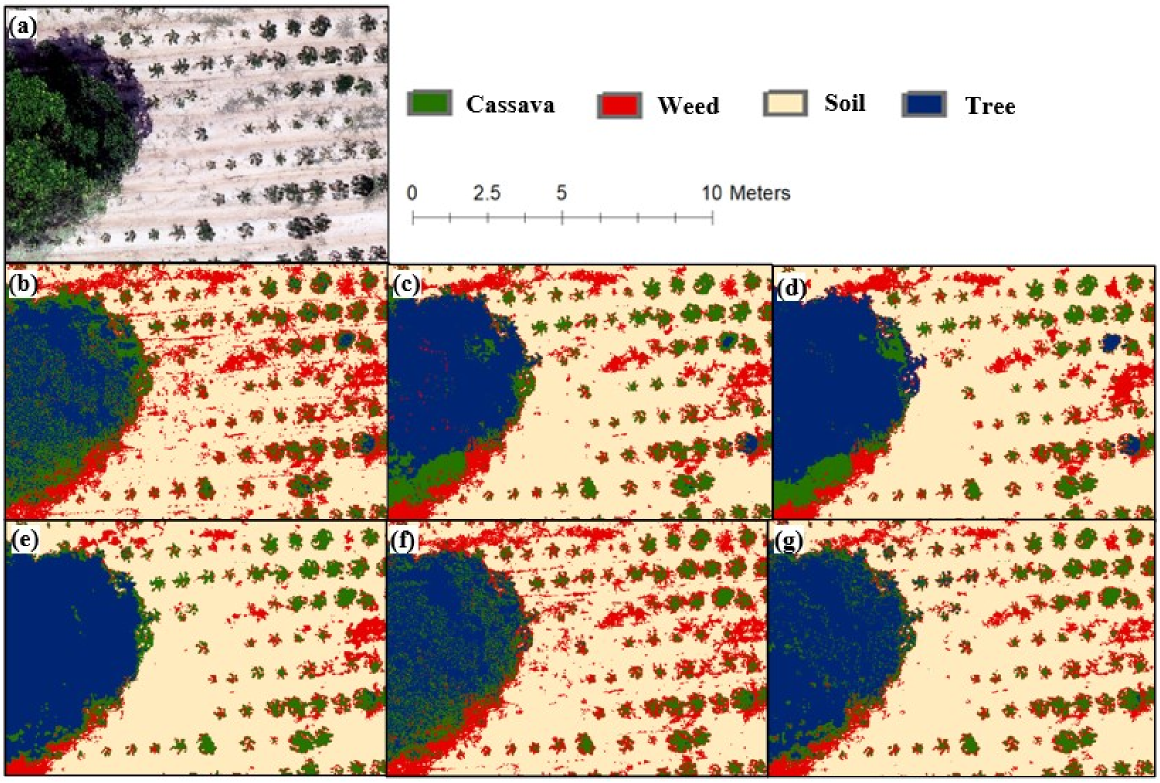

Figure 7 Original RGB image (a) and classification results from unfiltered image (b) and filtered image (c-g). Mean-shift parameter: (c) sp20 sr30, (d) sp20 sr40, (e) sp40 sr45, (f) sp80 sr15 and (g) sp60 sr30.

4. Discussion

In this study, two significant parameters of the mean-shift filtering are spatial window size (sp) and color window size (sr). As the experiments, changing sr shows the diversity of the image. The sr can reconcile the pixel according to the small objects that are eliminated. The result of the filtering process can lose some information, which is expected as noise and outlier data. These are reduced the quality of input data and affect clustering and classification analysis. The mean-shift filtering process can removed them and improved the classification results. However, the mean shift filtering can cause the blurring effect as shown in the Figure 4 when the sp and the sr are set with high values.

In comparison, spatial window size (sp) affects the size of the objects. The experimental results shows that the different mean-shift parameter values result in different precision value for each class. Thus, the best parameter values for each object vary regarding the size and pixel value of the object. This exploration confirms the concept of the scale parameter setting in the segmentation approach (Torres-Sánchez, López-Granados, & Peña, 2015).

The non-complexity of data from a few land-use types performs well in the SVM classifier with the mean-shift filtering due to the fundamental characteristics of these integrations. Although the mean-shift filtering is an additional process to a typical classification procedure, the optimum parameter values of sp and sr would be explored particularly for classification on the high-resolution image.

5. Conclusion

This study presents a discrimination technic for weed mapping in cassava fields by using the mean-shift filtering with the applicable parameters. The experimental results confirm that applying a mean-shift filtering method in the input RGB image can generalize the pixel values of the objects on the high-resolution image. Regarding spatial window size and color window size, these significant parameters would be considered to enhance the accuracy of the classification. As a result, appropriate parameters can increase the classification accuracy up to 4% from the RGB pixel-based classification. Regarding the properties of the high-resolution image from the UAV, it contains fine spatial and spectral resolution, which are too many details to classify a few land-use types, such as agricultural areas. As an accurate result of land-use classification, it can also be used to estimate a more accurate crop yield. Therefore, this experimental result can be applied to larger agricultural areas with several significant benefits, such as herbicide control, harvesting management, and yield estimation.

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