CHAPTER V
CONCLUSION AND SUGGESTIONS

This chapter presents the summary of the findings and results of the study. This study was undertaken to design a semi-automatic classification process for classifying objects in cassava fields from very high-resolution UAV images. The summary of results includes the finding in developing the classification process, the results of adjusting and validating the classification process, and the result of applying the adjusted proposed classification process in the study areas. Moreover, this chapter provided suggestions for the study for future work. Details are described as follows.

5.1 Conclusion

In this experiment, various RGB and RGB-based indices were applied as input for the classification image. The images were taken from UAV which contained very-high spectral resolution and various color values; the image needs to be enhanced to reduce the heterogeneity and noise for other processes. The selected method for enhancing images was mean-shift filtering. The three layers from RGB and indices were combined to produce a three-layer image that matched the requirement of the mean-shift filtering algorithm. According to the classification results, different classes reached high accuracy when applying different combination images. Therefore, the combination of indices was evaluated as a significant feature of the classification process.

In the process of adjusting parameters, various indices demonstrated their performance in separating classes. The Color Index (CI) emerged as a reliable index for soil classification, effectively differentiating soil from other elements in an image due to its sensitivity to soil color and composition (Escadafal and Huete, 1991). Notably, the CI index is less influenced by vegetation cover, making it valuable for distinguishing between soil and vegetation.

For tree classification, the VARI index proves to be a valuable tool. It accounts for atmospheric conditions and illumination variations, which can impact reflectance measurements. By enhancing sensitivity to vegetation, the VARI index improves discrimination among different types of vegetation and other land cover categories.

The Green and Excess Red (ExR) indices play a crucial role in differentiating cassava and weed. The green band reflects the green light absorbed and reflected by plants, enabling discrimination based on leaf structure, density, and pigmentation. The ExR index measures the excess red light reflected by plants compared to their reflectance in the green band, aiding in distinguishing plant species with varying chlorophyll absorption properties (Virtanen et al., 2022).

The application of mean-shift filtering aimed to improve image quality by adjusting parameters to find an appropriate set. The adjusting and validating classification process results demonstrated that using suitable parameters allowed for the quick and accurate detection of interesting objects. The filtering process effectively detected differences in spectral value and size, underscoring the importance of selecting optimal parameter values to achieve the best results.

In soil classification, the optimal values for *sp* and *sr* were determined to be 5 and 10, respectively. The use of various *sp* values resulted in high accuracy, indicating the soil class's lack of a well-defined shape, making it difficult to determine the exact *sp* value. Conversely, employing a small *sr* value yielded high accuracy allowing for better differentiation between vegetation and soil by considering the narrower spectral range of the combined indices used.

In tree classification, higher accuracy was achieved using larger values of *sp* and *sr* in the filtering process. For the first filter, a *sp* value of 60 and a *sr* value of 20 were found to be optimal, while for the second filter, a *sp* value of 20 and a *sr* value of 40 yielded good results. These findings suggest that the size of the filtering window should correspond to the size of the tree canopy. Given that tree canopies are typically larger, using a larger *sp* value effectively smoothed the tree pixels. Additionally, trees exhibit a wider spectral range than other classes within the same index, making a higher *sr* value advantageous for smoothing tree pixels.

The selected filtering window size parameters for cassava and weed classification were *sp*=10 and *sr*=20. The *sp* parameter was specifically chosen based on a GSD of 5 cm and a spatial window of 10 pixels, aligning with the average size of cassava canopies ranging from 52 to 88 centimeters. This finding indicates that the *sp* parameter is related to the size of the targeted object. Additionally, the *sr* parameter was responsive to the spectral values of cassava in the indices, further enhancing the accuracy of the classification.

K-means clustering was utilized for classifying different classes, demonstrating its potential in extracting and separating these classes. The number of clusters (*k*) played a crucial role in controlling the clustering outcome, making it essential to adjust this parameter correctly. This study designs cluster results consisting of four clusters: cassava, weed, soil, and tree. However, achieving accurate classification for all classes in a single attempt was challenging, necessitating separate or hierarchical processes. For soil classification, *k*=3 was used to separate soil, vegetation, and background data. In tree classification, *k*=3 was employed to cluster tree, non-tree, and background. Lastly, cassava and weed classification utilized *k*=4 to classify cassava, weed, pixels of soil and tree, and background data. The cluster results were influenced by the number of clusters and the properties of input data, as evident from the variations observed in the classification outputs with different input and image sizes, even within the same area.

The spectral properties of the clusters varied, with the centroid of each cluster being influenced by the input data. Different combinations of indices resulted in distinct centroid values even within the same class. The spectral value trends were flexibly applied to label the classes to accommodate different input images and study sites with varying DN values due to light conditions. For labeling the soil class in image of GSD 5 cm, the trend of the cluster's spectral value centroid in index B was utilized, where the cluster with high values was labeled as soil and the rest as vegetation.

The spectral value centroid in the ExB index was used in tree classification, with low values labeled as tree and the remaining as non-tree. As for labeling cassava and weed, the G index was employed, where cassava exhibited low G values and weed showed high G values.

The results obtained from adjusting and validating the classification process highlight the importance of using different parameters for classifying objects in the fields. Objects in the fields have distinct sizes and spectral properties, necessitating specific parameters for accurate identification and analysis. Additionally, the accuracy of the classification results is influenced by the image's Ground Sample Distance (GSD). The image with finer GSDs tends to yield higher accuracy but requires more processing time. In contrast, a GSD of 5 cm demonstrates a comparable classification accuracy to that of a GSD of 1.5 cm, as evidenced by high values in OA and kappa coefficient, with a significance level of 0.05 determined by a t-test. Additionally, it significantly reduces processing time. Hence, employing an image with a GSD of 5 cm ensures both accuracy and time efficiency.

The performance of traditional classification methods: RF and K-means, were compared to the results obtained from the proposed classification process. The results from the proposed classification process showed significantly higher accuracy than the K-means method, as determined by a t-test at a significance level of 0.05. In contrast, the proposed classification process yielded high accuracy comparable results to RF. Furthermore, the proposed process demonstrated a reduced requirement for manual intervention and user-provided data.

The proposed classification process was evaluated in 12 distinct cassava plots, employing two approaches: processing the entire area and splitting the image into two pieces. For most plots, both approaches produced comparable levels of accuracy. In the four-class classification, the highest accuracy achieved was 0.8217 for OA and 0.7445 for the kappa coefficient. For the three-class classification, the accuracy reached 0.9867 for OA and 0.9800 for the kappa coefficient. On the other hand, employing the split image process led to improved accuracy. Specifically, in specific plots, the implementation of this approach resulted in a notable increase in accuracy, with improvements of 0.1195 for OA and 0.1786 for the kappa coefficient.

The study's findings reveal that the proposed classification process successfully identified soil and trees. However, it demonstrated lower to moderate accuracy in identifying cassava and weed. The study suggests that the classification process may encounter difficulties in areas with varying canopy sizes, diverse weed invasion, and lighting conditions. Splitting the input image into smaller segments can improve accuracy by handling local differences. However, it's important to consider that the results can still be affected by lighting conditions and the level of weed invasion in the image.

This study demonstrates that using color indices, mean-shift filtering, K-means clustering, and rules can effectively classify and generate weed maps in cassava fields. One advantage of this approach is its ability to detect different vegetation species using images captured by various RGB sensors. Additionally, the classification method does not rely on training data, allowing it to be applied to different areas of cassava images. The parameters in the proposed classification process were carefully chosen to suit the classification objectives in cassava fields. Furthermore, the proposed classification process encompasses preprocessing and weed classification, reducing the need for extensive manual intervention. Lastly, the method operates in a semi-automatic manner, making it suitable for applications in precision agriculture.

5.2 Suggestions

(1) Cloud cover during UAV flights can affect image illumination, potentially leading to misclassification in the results, as seen in plot 8. It is recommended to avoid capturing images in cloudy conditions. To improve classification accuracy, it is advisable to capture images around noon to minimize the impact of shadows.

(2) The analysis of the classification results demonstrates that plots with varying levels of weed invasion in cassava substantially impact classification accuracy.

Splitting the image into smaller sizes can enhance the classification results. Further testing is recommended to assess the effect of varying the size of the spliced images.

(3) The process of applying the proposed classification process to the image is shown in Figure 5.1. When the accuracy of classification results is lower than 0.7 or 70%, the image should split before classification.

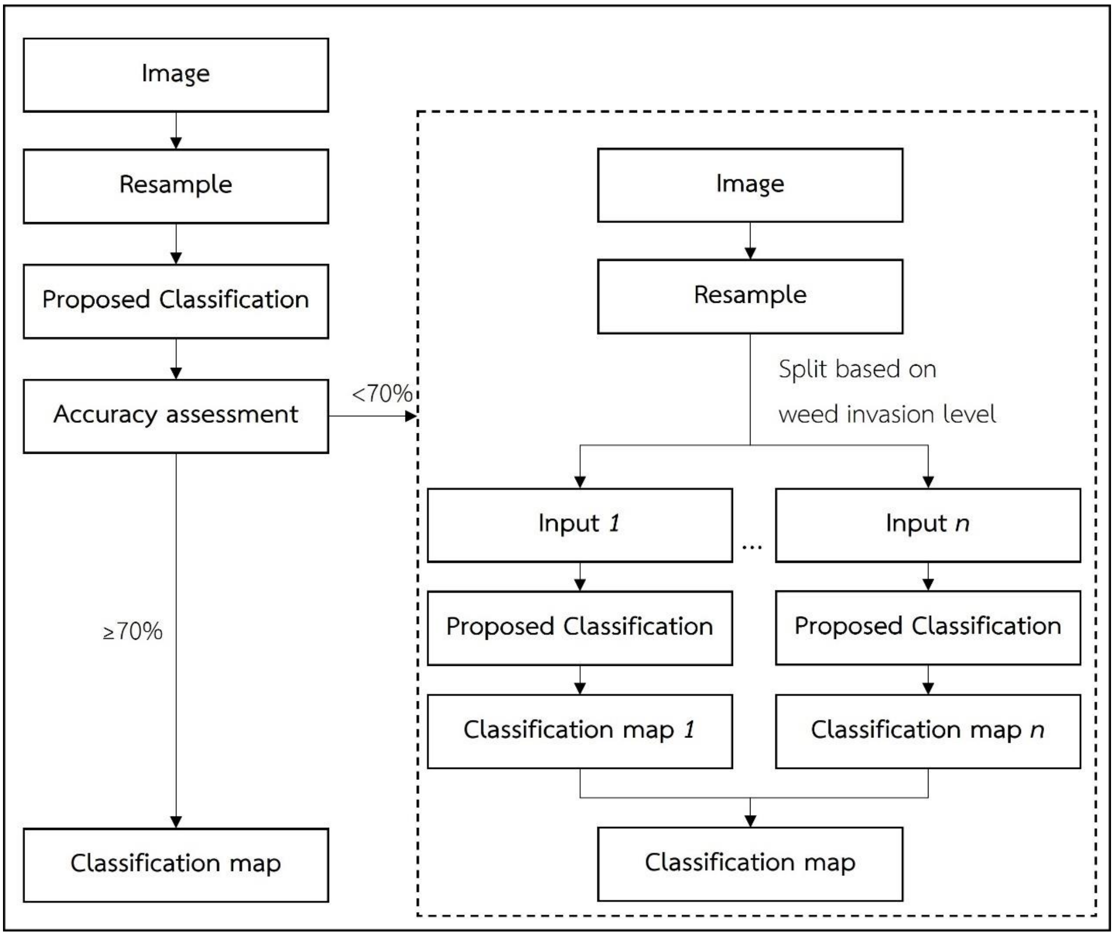

Figure 5.1 Classification process for processing the entire image and splitting image.

(4) Since the classification map can be integrated with other agriculture applications, such as spraying systems, which require accurate position. Therefore, the georeferencing process is needed. The ground control points (GCPs) should be applied during the image acquisition process.

(5) Although the coordination of weed patches can be identified and transferred to applicable with the drone service, personal accessibility is essential to weed management in the cassava fields. A guiding map with row numbers representing the cassava row is necessary for this activity. Counting the row automatically with coding in Python would be possible by setting the rule to define the first canopy in cassava rows. Therefore, codes of row numbering on cassava maps are recommended for future work. This suggestion will be helpful to smart farmers who would like to access the weed patches to control the invasion areas.

(6) The proposed classification processes can also be applied to high-resolution satellite images for the semi-automatic classification of objects. By adapting the proposed processes to high-resolution satellite data, it becomes possible to get the advantages of remote sensing technology and extend the application of the classification method to a wider range of scenarios.

(7) For future studies, the automatic classification process can be enhanced by splitting the proposed classification process into two programs. One program can focus on classifying images of cassava plots that contain trees, while the other program can be dedicated to classifying images of cassava plots that do not contain trees. These enhancements can reduce the need for manually defining trees during the classification process.