Weed Species Identification Using Drones with Multispectral Cameras and Machine-Learning

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Abstract

In recent years, smart agriculture utilizing technologies, such as robotics, sensing, internet-of-things (IoT), and artificial intelligence (AI), has been promoted to address pressing challenges in agriculture, including the aging and shrinking human farming population, as well as the effects of global warming on crop production. As part of these initiatives, we are developing and implementing a method of weed species identification using drones equipped with multispectral cameras, as well as machine-learning, with the aim of reducing both time and labor. Weed species identification plays a crucial role in enabling environmentally-sustainable weed management by facilitating species-specific countermeasures. This is particularly important given the increasing impact of climate change, which has accelerated and prolonged weed growth and promoted the spread and establishment of invasive species, thereby adversely affecting crop yields.

Keywords

Smart Agriculture, Multispectral Camera, Machine-Learning, Weed Species

1. Introduction

In recent years, smart agriculture has been promoted through the use of robotics, sensing technologies, internet-of-things (IoT), artificial intelligence (AI), and other innovations to achieve labor-saving, high-yield, and high-quality crop production [1]. Various technologies are being developed to address the pressing challenges facing Japanese agriculture, including the declining and aging human farming population and the impact of global warming on crops. As part of these efforts, we are developing a method for rapid and low-effort weed species identification using unmanned aerial vehicles (UAVs) equipped with multispectral cameras and machine-learning, a core technology of artificial intelligence. Weed species identification plays a key role in implementing targeted measures as part of Integrated Pest Management (IPM), a strategy that combines chemical, cultural, and physical control methods to minimize environmental impact while maintaining weed populations below economically-damaging thresholds [2]. This is especially important in light of the earlier and prolonged growth of weeds and the increasing spread and establishment of invasive species due to climate change, both of which pose serious threats to crop productivity. Weeds compete with crops for essential resources, leading to

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reduced yields. Therefore, effective weed management practices are essential to maintaining crop productivity and promoting sustainable agriculture. Monitoring the use of UAVs has proven effective for the early detection of invasive weeds and for large-scale environmental observations [3]. In particular, combining UAVs with object-oriented image analysis enables high-accuracy and efficient vegetation mapping in semi-natural grasslands [4]. In the current study, we measured the spectral reflectance characteristics of weeds using UAVs and classified the species using machine-learning [5]. For quick and easy weed species identification, weed species were classified using a Random Forest model trained on the clustering results [6, 7, 8, 9]. These indices are expected to enable faster and more accurate discrimination than conventional methods. The remainder of this paper is organized as follows. Section 2 describes the vineyard plots, observation methods, and the classification approach using existing technologies. Section 3 presents the conclusion and discusses future work.

2. Development of methodologies for weed species identification

2.1. Research plots

The study was conducted in three vineyard plots located in Takizawa City, Iwate Prefecture, Japan. Plots 1 and 2 were situated on sloped terrain, whereas Plot 3 was located on flat land (Figure 1). Plot 1 was expected to yield its first harvest in 2024. Plot 2 was a newly-developed site that had not yet been planted and was a vacant field, whereas currently contained young grapevines under cultivation. The grape varieties cultivated in these plots were Cabernet Franc [10], Sauvignon Blanc [11], and Trousseau [12, 13]. Various weed species had been identified in the study areas, including clover, horsetail, dock, and kudzu. These weeds require similar resources to grapevines, such as sunlight, soil moisture, and nutrients, and therefore compete with the vines for these limited inputs. Without appropriate weed management, such competition can inhibit grapevine growth and potentially facilitate the spread of pests and diseases. For instance, clover (Figure 2) absorbs nitrogen from the soil; horsetail and dock (Figure 3) serve as potential hosts for insect pests, such as the Japanese beetle and the false Japanese beetle; and kudzu (Figure 4) develops extensive underground root systems, making soil preparation extremely challenging. However, clover is also known to have beneficial effects. It is generally recognized that reducing soil moisture content and nitrogen availability can enhance the sugar concentration (Brix) of grapes [14]. Clover is sometimes intentionally used in vineyards as a soil moisture regulator as green manure due to its ability to fix nitrogen in root nodules and as a soil erosion control measure, due to its strong and widespread root system.

2.2. Weed species classification using non-hierarchical clustering

This approach combines existing technologies to propose a method for simple and rapid classification. The drone used in this study was the DJI Mavic 3M (DJI, Shenzhen, China) (Figure 5) [15]. Aerial imagery was acquired on three occasions in 2024: July 2, July 23, and September 22. The flight altitude was maintained at approximately 50 m for all sessions; image acquisition was avoided during rainy conditions. After generating orthomosaic images, the target areas were trimmed using GIS software (QGIS) [16]. A mesh size of 1 m^2 was applied, and the spectral

Figure 1: Aerial photo of the surveyed vineyard plots in Takizawa City, Iwate Prefecture, Japan

Figure 2: Clover (2024/7/2)

Figure 3: Kudzu (2024/7/2)

Figure 4: Horsetail/Dock (2024/7/2)

Figure 5: The unmanned aerial vehicle used in the trial (DJI Mavic 3M)

characteristics of weeds within each mesh unit were analyzed based on the reflectance values in each wavelength band. Plant reflectance was characterized by pronounced differences in the red (R), red-edge (RE), and near-infrared (NIR) bands (Figure 6). Healthy leaves exhibited low reflectance in the red and green bands and high reflectance in the NIR band, whereas withered leaves showed increased reflectance in the red and green bands and reduced NIR reflectance (Figure 6). Soil demonstrated uniformly low reflectance across all bands [17]. Based on the clustering results of the three sets of aerial imagery and corresponding field surveys (Figure 7), characteristic spectral features were identified for kudzu, clover, and dock/horsetail. Weed species were actually observed and surveyed in the fields to identify which weed species were growing in each mesh unit. Kudzu, which is vigorous and enters its flowering phase in summer, produces large leaves. As a result, during summer, its NIR reflectance reached values approximately ten times higher than its red reflectance; green reflectance was higher than that of clover and dock/horsetail. Clover exhibited NIR reflectance approximately five times greater than red, but with lower green reflectance than measured in kudzu. Horsetail/dock had an NIR reflectance approximately three times higher than red, and its green reflectance was comparable to that of clover.

Figure 6: Differences in spectral reflectance depending on leaf health

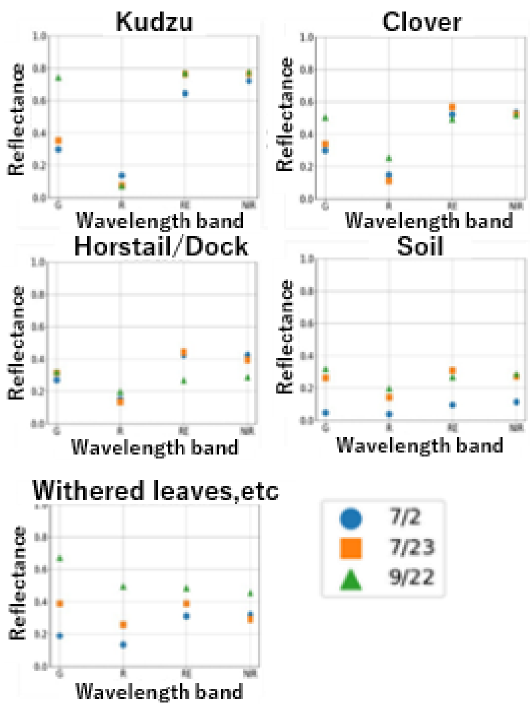

Figure 7: Average reflectance of each wavelength band for each cluster is the average of the data taken from three aerial photos data on different days

The near-infrared (NIR) band exhibited the highest feature importance when classifying all weed species using a Random Forest classifier trained on the clustering results from July 2 as training data (Figures 8, 9). The red edge (RE) band also showed high importance, particularly for horsetail/dock. In contrast, the green (G) and red (R) bands demonstrated relatively low importance, with only minor variation across species and limited overall contribution. This ranking of feature importance was consistent across multiple evaluation metrics, including feature importance, permutation importance, and Shapley additive explanations (SHAP) values, with NIR consistently ranked highest, followed by RE, then G and R. These results confirm that NIR and RE are the most effective spectral bands for weed species classification. A breakdown of SHAP values by species indicated that for clover, although the overall contribution of features was relatively modest, NIR remained the most influential. In the case of kudzu, both NIR and RE values were important, indicating their substantial role in its identification. For dock/horsetail, SHAP values for NIR and RE were even higher, suggesting stronger discriminative power. These differences are attributed to the distinct spectral reflectance characteristics of each species. NIR and RE wavelengths are particularly sensitive to factors such as plant moisture content, physiological health, and structural traits, making them effective for capturing interspecies variation. Conversely, the G and R bands had relatively limited impact and may even negatively affect classification accuracy for certain weed types. The trained classifier was then evaluated using aerial imagery captured on July 23 and September 22 as test data. Figure 10 shows the actual weed species distribution data for July 23, whereas Figure 11 presents the classification results generated by the Random Forest model. The model achieved an accuracy of 90.9%, indicating strong performance. Figures 12 and 13 show the actual weed species distribution data and classification results, respectively, for the September 22 data, with an accuracy of 82.8%. These findings demonstrate that a generalizable classifier can be effectively trained using clustering-based labeling as training data.

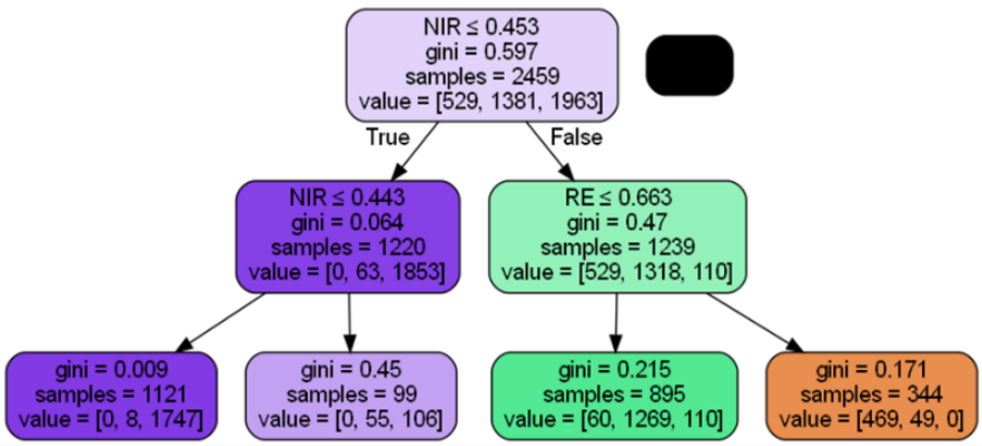

Figure 8: Decision tree for all wavelength bands.

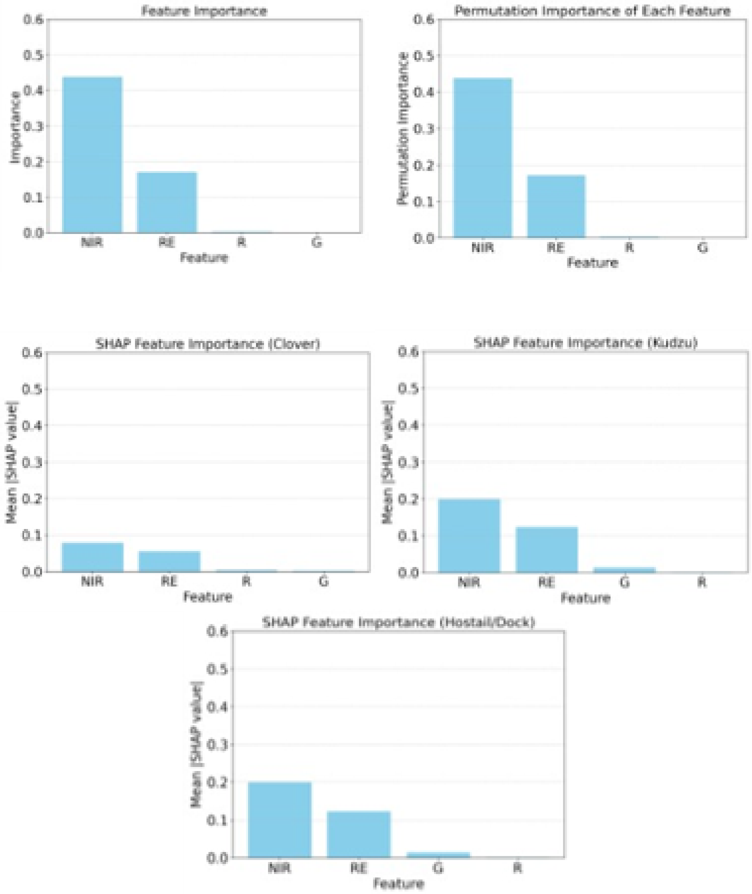

Figure 9: Analysis using feature, permutation, and SHAP importance

3. Conclusion

This paper presents the development of a rapid and low-effort method for weed species identification using a drone equipped with a multispectral camera in combination with machine-learning. This approach combines existing technologies to propose a method for simple and rapid classification. Accurate identification of weed species enables the implementation of species-specific management strategies, thereby contributing to reduced environmental impact. The evaluation experiments demonstrated that the proposed method permitted effective and straightforward diagnosis. The weed species observed in this study exhibited distinct spectral reflectance characteristics, suggesting that these features can be utilized for their identification in other fields. Future work includes expanding the range of measurable spectral bands to achieve more detailed diagnostics, as well as conducting further validation across a greater number of vineyard plots to evaluate the generalizability and practical utility of the approach. Integrated pest and weed management (IPM) is increasingly promoted as a means of reducing environmental burden, and the method developed in this study is intended to contribute to such initiatives through

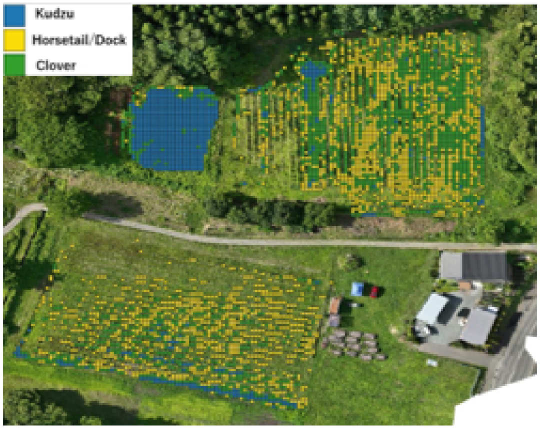

Figure 10: Actual weed species distribution data (aerial photo taken on 7/23/2024)

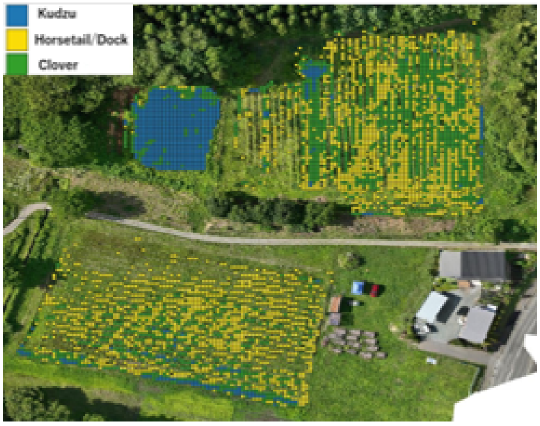

Figure 11: Classification results generated using the Ran-dom Forest model (aerial photo taken on 7/23/2024)

Figure 12: Actual weed species distribution data (aeri-al photo taken on 9/22/2024)

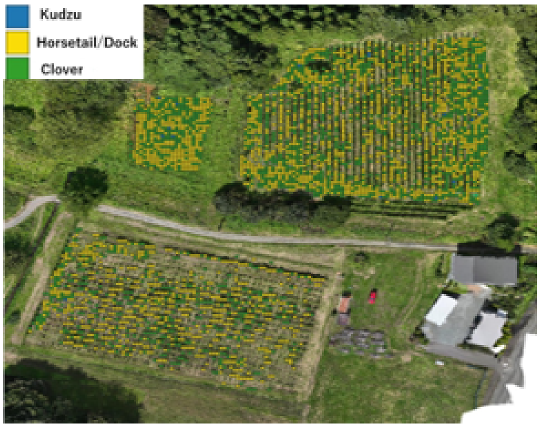

Figure 13: Classification results generated by the Random Forest model (aerial photo tak-en on 9/22/2024)

practical deployment.

Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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