USING DRONE-BASED THREE-DATE MULTISPECTRAL IMAGES TO CLASSIFY INVASIVE ALIEN SPECIES WITH MACHINE LEARNING ALORITHMS

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ABSTRACT: In the past few decades, globalization has caused invasive alien species (IAS) to spread to the world, and IASs have damaged local agriculture and ecosystems. *Leucaena leucocephala* (white popinac, WP), a world-famous IAS, is chosen as target species. WP can blossom and fructify throughout the year, and its phenology is affected more by precipitation rather than different seasons. Hence, we conducted our field survey to collect in-situ data in dry, rainy, and normal seasons, and also used drone to take three-date multispectral images (five spectral bands). To ensure the data quality, we used centimeter-grade Trimble R12 to measure six ground control points, and the final orthophoto's resolution is 6 cm, with the positioning error of 2.7 cm. We used logistic multiple regression (LMR), random forest (RF), and light gradient boosting machine (LGBM) to classify WP and used F1 score and *kappa* coefficient to assess model performance. In dry season, reflectance in green and near-infrared (NIR) band are the lowest. When using three seasons separately, the normal season's accuracy is the highest, F1 score and *kappa* coefficient of LGBM was 0.91 and 0.87. And by combining three seasons together, the accuracy got improved again. LGBM's index value was 0.97 and 0.95, showing that combining data from different dates could boost classification accuracy. As for the contribution of different bands in spectrum, NIR band from dry and normal seasons contributed the most. Red band from normal and rain seasons were also important, showing that red and NIR bands are important for classification. In conclusion, this research confirmed that WP's phenology is affected by precipitation and understanding the effect of dry and rainy seasons can enhance the accuracy of models. By combining data from three seasons, models would provide the highest accuracy, showing that multi-temporal data could boost model performance.

INTRODUCTION

Invasive alien species (IAS) had become much easier to spread due to the prosperous globalization and would be very threatening to local species. IAS would be difficult to wipe out once it had established a study bridgehead. Hence, whether the authorities could detect IAS in time is the key to prevent IAS from spreading. In the past few decades, this work was done by field survey or with satellite-based or airborne images, but field survey couldn't cover large areas and the spatial resolution of satellite-based or airborne images were too low to identify IAS's forerunners. Also, these two remote sensing platforms are not mobile enough to evade the influence of weather and clouds. On the other hand, the high mobility of unmanned aerial vehicle (UAV) made it a handy tool to conduct survey any time the researcher wanted to, while providing images with high spatial resolution. Hence, this research focuses on using UAV with multispectral sensor to obtain multi-temporal images of *Leucaena leucocephala* (white popinac, WP), a wide-spreading IAS, trying to figure out the key feature to classify WP from other plants.

METHODS AND MATIRALS

Study Area

The study area is situated in Guoxing Township, Nantou County of central Taiwan (Figure 1). Its area is 12.05 ha, the terrain is flat and broad. The elevation of the area is around 250m. Table 1 shows the average temperature and precipitation of Guoxing. The maximum mean temperature is 27.6 ℃, while the minimum is 16.5 ℃. The maximum precipitation is 821 mm in October, and the minimum is 16 mm in December.

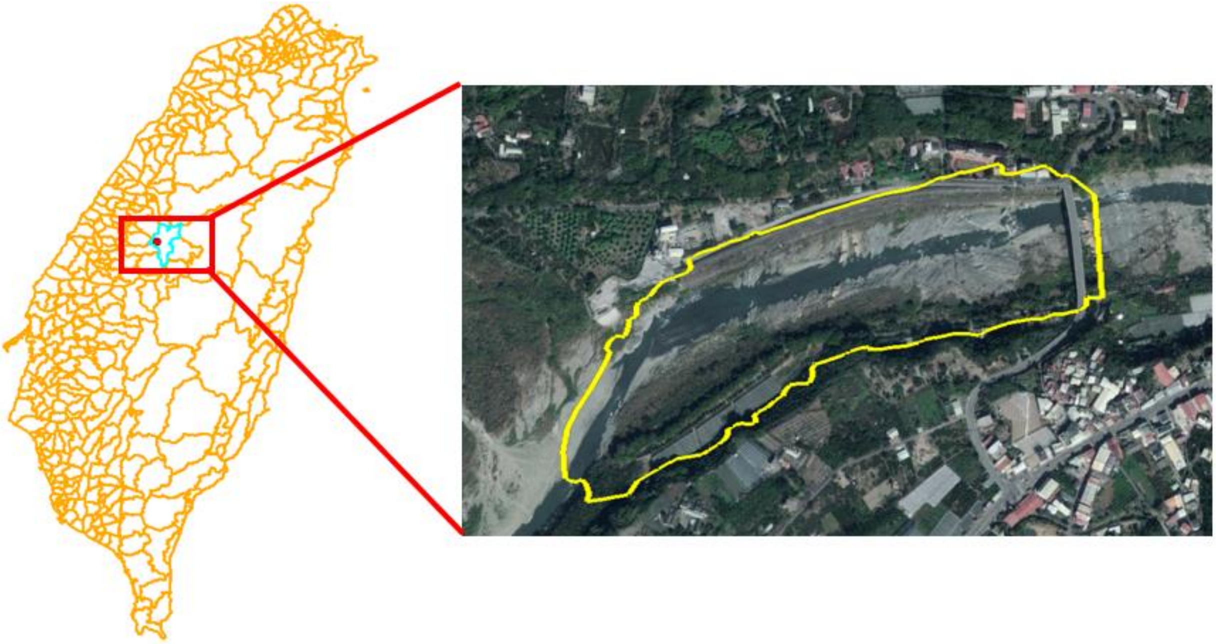

Figure1 Study Area

Table 1 Monthly Average Temperature and Rainfall of Guoxing Township

Date	2021 May	2021 June	2021/ July	2021/ Aug.	2021/ Sept.	2021/ Oct.	2021/ Nov.	2021/ Dec.	2022/ Jan.	2022/ Feb.
Temperature (℃)	27.4	25.8	27.7	26.5	27.6	25.7	21.6	17.6	17.4	16.5
Rainfall (mm)	334.5	741.5	265.0	821.0	108.5	27.0	17.5	16.0	54.5	138.5

Target Species

Leucaena leucocephala (white popinac, WP) is an IAS that prefer places with sufficient sun light (Figure 2). It could blossom and fructify throughout the year, giving it an advantage over other species. Moreover, it could spread mimosine, a toxic compound, to suppress other plants' growth even to death, further ensuring its own dominance. For WP's phenology, it could simultaneously blossom and fructify anytime in a year, and new seedpods could appear even before the old one fell. These observations suggest that WP's phenology is merely affected by different seasons.

Figure2 Photo of *Leucaena leucocephala* and its seedpods

According to previous studies (Chung and Lu, 2006), by calculating the ratio between short-wave infrared and near infrared (NIR), the researchers found out that WP at southern Taiwan have a significant difference of phenology between dry and wet seasons. Feng and Chen (2008) further studied the influence of different seasons on WP. They used hand-held spectrometer to measure the reflectance of WP and other plants, finding that red band and NIR band of autumn could separate WP from other plants. By combining these studies, we inference that WP's phenology is mainly affected by precipitation. When in dry seasons, WP's reflectance in green band and NIR band would drop, highlighting the difference of phenology between different seasons, further helping us to detect WP from background. Chung (2006) used SPOT 4 and SPOT 5 images to gain data at a large special scale, on the other hand, Feng and Chen (2008) used hand-held spectrometer to obtain accurate in situ data. Although Feng and Chen could obtain accurate spectral data, but it would be difficult to extrapolate to greater special scales. Hence, we need to use UAV to gain accurate reflectance data from different areas to understand the difference of our target species in different environments.

Data Collection and Processing

Our samples came from UAV-based multispectral images and in situ data collection. The model of UAV was DJI Phantom 4 Multispectral RTK, able to detect electromagnetic radiation of blue band, green band, red band, red edge (RE), and NIR band. Also, it could use real time kinematic (RTK) to strengthen its ability for accurate positioning, reducing positioning error of multitemporal images. Balancing between the efficiency of surveying and the spatial resolution, we set the fly height to 90 m and frontal overlap and side overlap to 80% and 70% respectively. As for measuring coordinates, we used Trimble R12 to obtain accurate data. Both our UAV and R12 used virtual reference station provided by the Ministry of the Interior to execute RTK positioning, giving us the accuracy of centimeter-grade. The study area's precipitation is mostly affected by terrain and monsoon. Most rain falls in summer and winter is dry in most times, so we conducted our survey in July and February to collect data of wet season and dry season. As a comparison, we also collected data in October for data standing for normal seasons. To ensure data quality, we placed six ground control points (GCP) in our study area.

As for image processing, we used structure-from-motion function of Pix4D to generate orthophoto from UAV images, and the final product's spatial resolution was 6 cm, with 2.7 cm of positioning error. Considering that images at the edges would likely contain some error due to the lack of overlaying images, we cut the inaccurate part to ensure the overall accuracy. We divided ground cover into seven types: WP, other plants, path, rock, water, shading nets, and asphalt. We extracted 8,000 samples in total. For model training and validation, we set 90% of samples as training data and 10% as validation data, and we used F1 score and Cohen's *kappa* for model assessment.

Machine Learning Algorithms

In this study, we used three algorithms to classify WP: logistic multiple regression (LMR), random forest (RF) and light gradient boosting machine (LGBM). LMR is a non-linear model, mainly used to deal with classification. This is a particular case if generalized linear model and an important progression of statistics in the past three decades.
LMR is a basic binary linear classifier that uses a sigmoid function or a logistic link function to take a simple linear equation as a parameter. It would compress the range of linear equation's output from zero to one and will give the probability of data classification (Hosmer and Lemeshow, 2000). RF is an ensemble classifier, and its stability was already proved. Furthermore, RF has a good tolerance of inevitable noise and outliners in ecology, making it unlikely to be over fitting. This algorithm would establish various randomized decision trees and integrates the prediction of each decision tree by averaging them (Breiman, 2001). LGBM was created by Microsoft in 2017. Based on gradient boosting machines, the engineers used gradient-based one-side sampling and exclusive feature bunding for optimizing. As the result, they successfully shortened training time and resources used. Both LGBM and RF are ensemble classifiers, but RF uses bootstrap-aggregation to construct decision trees and LGBM uses boosting to do so. LGBM's decision trees are corresponding with others and would distribute the weight due to their misclassifications. In this way, LGBM could gradually correct the next decision tree if the previous one misclassified and overcome with the problem of overfitting (Boehmke and Greenwell, 2019).

RESULTS AND DISCUSSION

Descriptive Statistics

Figure 3 shows the difference of grey scale between different seasons and different bands. The reflectance of WP in visible light is similar to other plants, meaning that we can't classify WP from other plants by using visible light only. But as soon as we included RE and NIR bands, the differences between seasons were highlighted. When in dry seasons, WP loses chlorophyll α and β that would reflect green light. Focusing on the reflectance of NIR band, we found that the reflectance is the highest in normal season and the lowest in dry season, and this might be related to rainfall. After irrigation, WP would be covered by newly grew leaves, hence boosting the reflectance of RE and NIR. On the other hand, WP would lose leaves in dry seasons, therefor the brown seedpods were exposed, and the reflectance of NIR band reduced. As table 1 shows, the standard deviation (STD) of RE and NIR band are higher than three other bands, corresponding with the complex phenology of WP.

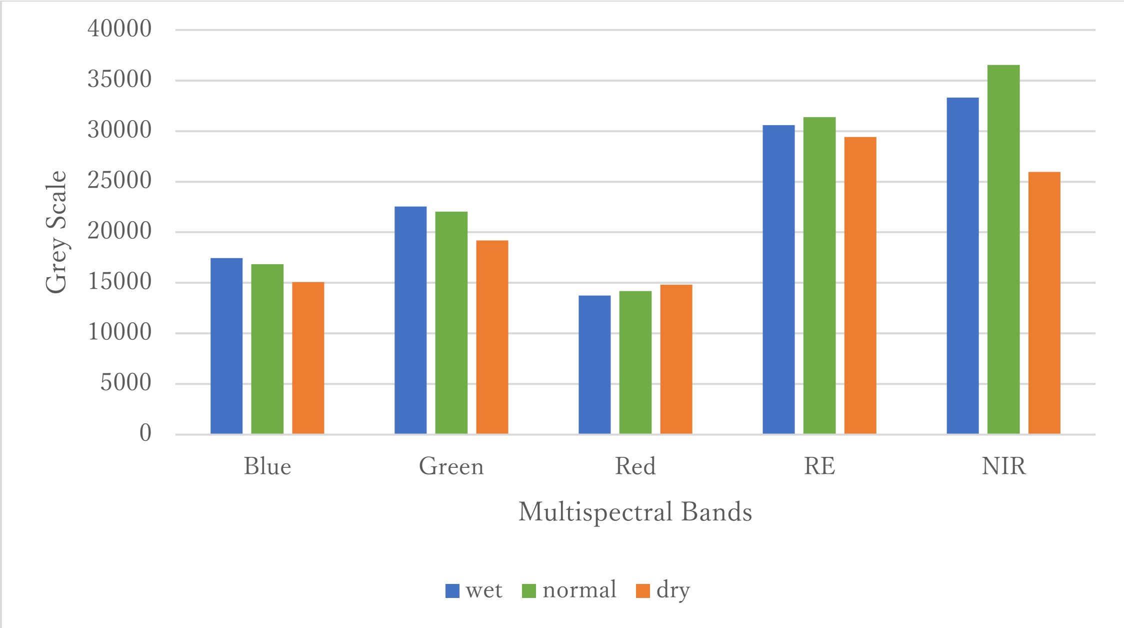

Figure 3 WP's Reflectance in Different Seasons

Table 1. The Three-phase Image Gray Value Description Statistics Table of WP

Seasons		Blue	Green	Red	RE	NIR
wet	mean	17455	22561	13746	30605	33322
	STD*	5387	8395	4713	9763	8608
	maximum	38710	46348	34500	52698	53415
	minimum	7000	5631	4978	6031	8136
normal	mean	16855	22052	14190	31371	36534
	STD*	4560	7226	3632	7603	7430
	maximum	32988	44379	28928	51109	55173
	maximum	7723	6704	5456	10017	11597
dry	mean	15080	19203	14829	29408	25977
	STD*	4503	7365	5322	8189	8332
	maximum	39103	48090	50725	53302	55857
	minimum	7080	7524	6438	9169	8390

*STD stands for standard deviation

The grey scale of other ground cover types is showed in Figure 2. For other plants, their reflectance was generally lower than WP, and the difference between seasons wasn't significant. The reflectance of shading nets in visible bands were higher than RE and NIR, this was because the net was made from white knitted yarn mesh. The paths were covered with sand and dry dirt, so the reflectance in visible bands was high. The roads and the embankments were covered with asphalt that would absorb lots of energy, therefor their reflectance was generally low. The reflectance of rock was highly correlated with its color and mineral. Rocks in the study area mainly contained minerals with darker color, therefor lowering their reflectance. Water would absorb energy from RE and NIR band and reflect energy from blue and green band. The difference of water's reflection between different seasons was due to its color, if water was whiter in the image, then its reflectance would be higher and vice versa.

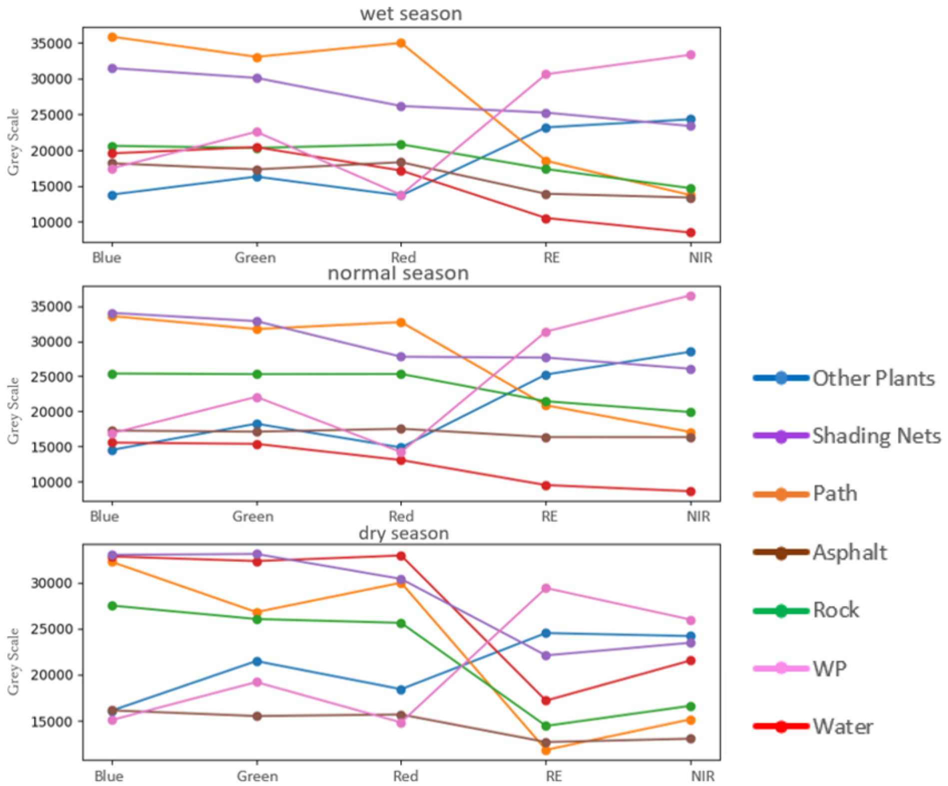

Figure 4 Reflectance of Different Ground Cover in Different Spectral Bands

Multispectral Bands

In order to investigate the importance of every band, we used XGboost to calculate the contribution of every feature. As figure 5 shows, NIR band of normal and dry season were the most important, their contribution was 0.27 and 0.18 respectively. The red band of normal and wet season were important also, contributing 0.09 and 0.08 respectively, and other bands only contributed around 0.04. This result shows that NIR and red band are important for image classification of plants. Aside from precisely capturing the diversification of phenology, we should also take these two bands for a good use to improve model accuracy.

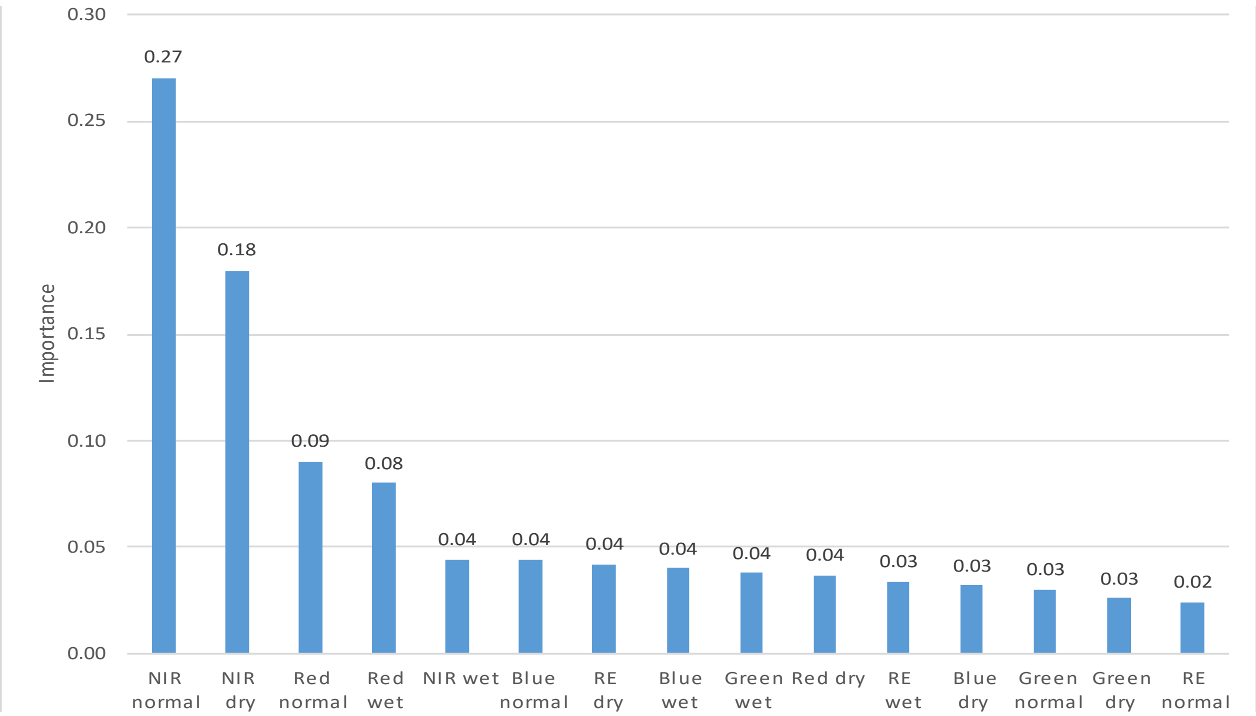

Figure 5 Importance of Different Spectral Bands

Multitemporal Image Classification

To compare the influence of different seasons on model accuracy, we exhausted every combination of seasons. Table 2 shows the result of using three seasons separately. Comparing to other seasons, normal season had the highest accuracy, its F1 score and *kappa* were both higher than 0.8, and the results of all models are more consistent. Between wet and dry season, the accuracy of wet season was slightly higher, and the model performance slightly diverged. Looking at the accuracy of training and validation data, training data gained higher accuracy, this meets general cases.

Table 3 shows the results of combining two seasons together. Overall, model accuracy was improved greatly from using one season only. The combination of wet and dry season provided the highest accuracy, showing that seasons with huge difference could boost model performance greatly. As for the performance of different models, we didn't find an obvious pattern, although they had some slight differences.

By combining three seasons together, we had the highest accuracy, the F1 score and *kappa* were both higher than 0.9 (Table 4). Also, the difference between training and validation data was much smaller than previous two methods, showing that multitemporal image could significantly boost the performance of classification.

Table 2 Model Accuracy of Three Seasons

		wet			normal			dry		
		LMR	RF	LGBM	LMR	RF	LGBM	LMR	RF	LGBM
training samples	*F1*	0.86	0.99	1.0	0.88	0.99	1.0	0.84	0.99	1.0
	kappa	0.77	0.98	1.0	0.81	0.99	1.0	0.76	0.99	1.0
validation samples	*F1*	0.87	0.90	0.90	0.88	0.90	0.91	0.82	0.90	0.89
	kappa	0.79	0.84	0.85	0.81	0.84	0.87	0.73	0.85	0.84

Table 3 Model Accuracy of Three Combinations

		wet & normal			wet & dry			Normal & dry		
		LMR	RF	LGBM	LMR	RF	LGBM	LMR	RF	LGBM
training samples	*F1*	0.93	0.99	1.0	0.94	1.0	1.0	0.92	1.0	1.0
	kappa	0.89	0.99	1.0	0.90	1.0	1.0	0.88	0.99	1.0
validation samples	*F1*	0.95	0.92	0.96	0.93	0.93	0.96	0.92	0.92	0.94
	kappa	0.92	0.88	0.94	0.90	0.89	0.94	0.88	0.87	0.91

Table 4 Model Accuracy of Three Combinations

		wet & normal & dry		
		LMR	RF	LGBM
training samples	*F1*	0.95	0.99	1
	kappa	0.93	0.99	1
validation samples	*F1*	0.95	0.94	0.97
	kappa	0.93	0.9	0.95

Algorithms

We used the confusion matrix (Table 5, 6 and 7) for a deeper comparison of the performance of three algorithms. In all kinds of ground covers, WP is mostly likely to be misclassified with other plants. This is because different WP could appear differently in the same season, making it challenging to identify. Hence, whether an algorithm could successfully separate WP and other plants is a key to assess its performance. Among three models, LGBM exceled at classifying WP, only had five and 10 samples of omission and commission error respectively. RF's performance was much worse, had 33 samples of omission error. Rock and shading nets were also easy to be confused. RF and LGBM only misclassified two and three samples of rock as shading nets, whereas LMR misclassified seven samples.

Table 5 Confusion Matrix of LMR

	WP	Asphalt	Shading Nets	Water	Rock	Path	Other Plants
WP	388	0	0	0	0	0	10
Asphalt	0	85	1	1	7	0	0
Shading Nets	0	0	31	0	0	0	0
Water	0	0	0	54	0	0	0
Rock	0	5	0	0	79	1	0
Path	0	1	0	0	0	62	0
Other Plants	14	1	0	0	0	0	60

Table 6 Confusion Matrix of RF

	WP	Asphalt	Shading Nets	Water	Rock	Path	Other Plants
WP	393	0	1	0	0	0	4
Asphalt	2	89	0	0	2	0	1
Shading Nets	1	0	27	0	2	1	0
Water	0	1	0	53	0	0	0
Rock	0	4	0	0	81	0	0
Path	1	0	0	0	0	62	0
Other Plants	33	1	0	0	1	0	40

Table 7 Confusion Matrix of LGBM

	WP	Asphalt	Shading Nets	Water	Rock	Path	Other Plants
WP	393	0	0	0	0	0	5
Asphalt	0	93	0	0	0	0	1
Shading Nets	0	0	27	0	3	1	0
Water	0	1	0	53	0	0	0
Rock	0	5	0	0	80	0	0
Path	0	1	0	0	1	61	0
Other Plants	10	0	0	0	0	0	65

CONCLUSION

This study confirmed that WP's phenology was affected greatly by rainfall. Also, the classification accuracy would improve significantly if using multitemporal images from different seasons. This shows the importance of understanding related knowledge of target species and the mobility of UAV. In the future, weather will become more and more unpredictable due to climate change, and only the highly mobile UAV can help researchers to capture the fleeting change of phenology.

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