TREE SPECIES IDENTIFICATION USING PRINCIPAL COMPONENT ANALYSIS FEATURES: AN ANALYSIS ON WHETHER NON-VEGETATION COMPONENTS SHOULD BE EXCLUDED

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Abstract. Principal component analysis (PCA) can reduce the dimensionality of high-dimensional remote sensing data. The layers obtained through its transformation have important applications in tree species identification. To investigate the performance differences in tree species identification between PCA extraction based on the entire image and based on the vegetation/tree part of the images containing a certain proportion of non-vegetation components. In this study, WorldView-2 and WorldView-3 data were used for comparison, maximum likelihood classification and support vector machine were used as comparative methods, and PCA layers extracted in different forms were used to classify tree species. The experimental results showed that: (1) PCA extraction based on the vegetation/tree parts of the image results in higher accuracy for tree species classification compared to PCA extraction using the entire image; (2) for images with a larger proportion of non-vegetation components, the difference in accuracy for tree species classification between PCA extraction based on the vegetation/tree parts and PCA extraction using the entire image was even greater. The study results indicated that for images with a large proportion of non-vegetation components, it is advisable to choose PCA transformation based on the vegetation/tree parts of the image when classifying tree species using PCA.
Keywords: *WorldView-2 and WorldView-3, image feature extraction, vegetation component retention, species classification, accuracy comparison, maximum likelihood classification, support vector machine*

Introduction

With the rapid development of remote sensing technology, high-spatial-resolution satellite images have become indispensable resources in the field of vegetation monitoring and tree species identification (Apostol et al., 2020; Carvalho et al., 2022; Kureel et al., 2022). The brightness of pixel clusters in remote sensing images can reflect the physical and biological attributes of surface cover, providing identifiable digital signals for ecological, forestry, and natural resource management. However, in practical applications, especially in complex urban and natural ecosystems, the images often contain a large amount of non-vegetation information, such as water bodies, buildings, roads, and bare soil (Liu et al., 2015, 2018). The presence of these non-vegetation components may interfere with the accurate identification of tree species, especially when they occupy a considerable proportion in the image.

In recent years, principal component analysis (PCA) has been widely used as an effective data dimensionality reduction method in remote sensing image processing and feature extraction (Ghosh and Joshi, 2014; Liu, 2024). Through PCA transformation, the original multi-band data can be converted into a few new layers, which usually contain more information and are independent of each other (Liu, 2024). Although PCA performs well in improving data processing efficiency and enhancing classification accuracy, optimizing the PCA layer extraction process for images with a large proportion of non-vegetation data to improve the accuracy and reliability of tree species identification remains an issue that has not been thoroughly explored. Since PCA is performed based on the correlation coefficient matrix or covariance matrix, non-vegetation components in the image significantly influence the correlation coefficients and covariances among layers. This, in turn, affects the differentiated representation of vegetation information in the principal component layers and ultimately impacts the accuracy of tree species identification.

At present, significant progress has been made in the application of remote sensing images in tree species identification, including algorithm optimization (Zhang et al., 2020; Yan et al., 2021; Kwon et al., 2023; Sun and Shi, 2023; Xu et al., 2024), feature selection (Masemola et al., 2020; Wang et al., 2020, 2022; Chen et al., 2023), selection of appropriate imaging time periods (Zhong et al., 2019; Pu and Landry, 2020; Shi et al., 2020; Liu, 2022; Nasiri et al., 2023), and multi-source data fusion strategies (Qin et al., 2022; Ferreira et al., 2024; Miraki et al., 2024). However, most studies focus on comparing algorithm performance or improving tree species identification accuracy in specific regions (Modzelewska et al., 2020; Marconi et al., 2022; Marinelli et al., 2022; Liu, 2023), and there is still a lack of systematic discussion on the potential impact of non-vegetation components in images on PCA processing and tree species classification accuracy. Additionally, with the widespread application of WorldView series satellite images, their high-resolution characteristics (e.g., WorldView-2 with eight bands, including blue, green, yellow, red, red edge, and near-infrared bands 1 and 2, with a spatial resolution of 0.5 m; WorldView-3, which adds eight shortwave infrared bands while retaining the same eight bands as WorldView-2, with a spatial resolution of 0.3 m) provide new opportunities (offering a relatively large number of spectral bands and emphasizing details of tree crowns) for accurate tree species identification (Liu and An, 2019; Liu and An, 2020), but they also pose new challenges related to the extraction of certain features from the images.

Given this, the current study selected two high-spatial-resolution images, WorldView-2 (WV-2) and WorldView-3 (WV-3), for tree species identification. The aim was to comparatively analyze the differences in PCA transformation for tree species identification between whole images and images with only the vegetation parts retained. The study employed two conventional classification algorithms, maximum likelihood classification (MLC) and support vector machine (SVM), which excel in low-dimensional data (Liu et al., 2015, 2022). Through comparative analysis, this research not only evaluated the impact of PCA layers extracted under different processing methods on tree species identification, but also delved into the variation in accuracy between different PCA extraction forms and the proportion of non-vegetation areas in the images for tree species identification. The execution of this study could provide valuable methodological guidance for using PCA in tree species identification, especially in complex scenes with a significant proportion of non-vegetation, where an appropriate PCA extraction method can maximize the accuracy of tree species identification.

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Material and methods

Remote sensing images and preprocessing

In this study, WV-2 and WV-3 were used for comparative experiments. Both WV-2 (Liu et al., 2018; Liu and An, 2019, 2020) and WV-3 (Liu, 2023) data were employed in previous research about tree species identification. It is worth noting that, although the WV-3 data originates from the same source as in previous studies, it does not cover the same area. For this research, the WV-3 image was extracted from a larger 25 km^2 image, focusing on Wangcheng Park (with band parameter settings detailed in *Table 1*), serving as the experimental data. Both images underwent preprocessing, namely radiometric calibration, atmospheric correction, and image fusion before use. Detailed preprocessing procedures can be referenced from previous studies (Liu et al., 2018; Liu and An, 2019, 2020; Liu, 2023). Regarding the WV-3 image, the cropped image (*Figure 1*) covers an area of 0.71 km^2, with a latitude range of 34˚39′51.15″–34˚40′17.25″ N and a longitude range of 112˚24′37.84″–112˚25′13.66″ E.

Table 1. *The multispectral and panchromatic bands spatial resolution and wavelength parameters of WorldView-3 imagery*

Band	Name	Pixel size (m)	Wavelength coverage (nm)	Central wavelength
1	Coastal Blue	1.24	400-450	425
2	Blue		450-510	480
3	Green		510-580	545
4	Yellow		585-625	605
5	Red		630-690	660
6	Red Edge		706-745	725
7	Near-Infrared 1		770-895	833
8	Near-Infrared 2		860-1040	950
9	Panchromatic	0.3	450-800	–

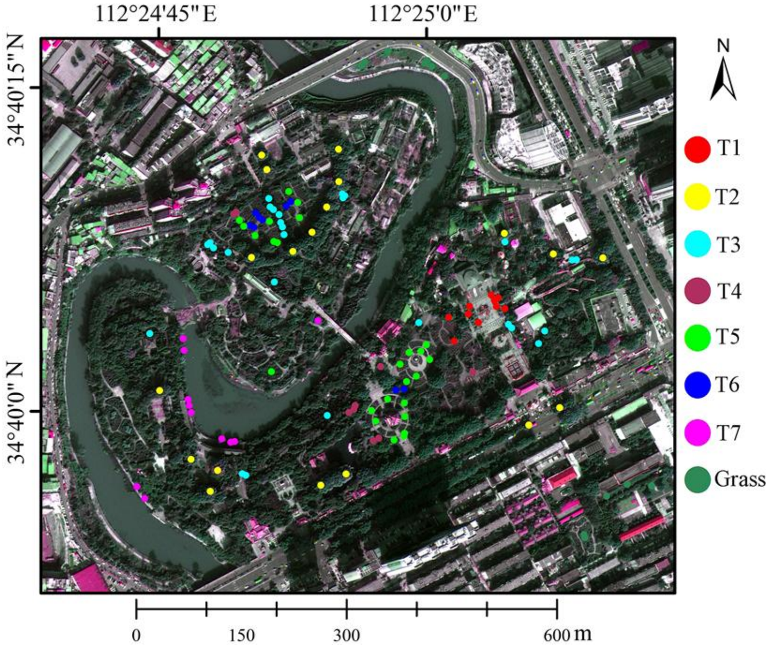

Figure 1. *WorldView-3 image of the study area (RGB vs 534). The spatial distribution of 7 tree species were marked with different colors in the imagery (T1- T7 represents 7 tree species)*

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Collection of tree species samples

The WV-3 imagery of Wangcheng Park was synthesized into a true-color image (RGB vs bands 532) and printed out for carrying out a field survey of tree species. On August 8th, 2020, a survey was conducted to identify typical tree species in this park. During the survey, the typical tree species distributed in the image were found in the real environment. After verification, their species names were recorded on the printed image. The survey was concluded after collecting sufficient tree species samples. Upon returning to the laboratory, the surveyed tree species were immediately marked on the image in the form of region of interest (ROIs) in ENVI, referencing the markings made on the paper image. During the marking process, some samples were selected as training samples, while others were chosen as accuracy validation samples. The distribution of various tree species samples (validation samples) on the image and the number of pixels collected are shown in *Figure 1* and *Table 2*, respectively. The process of collecting WV-2 samples is described in previous studies (Liu et al., 2018; Liu and An, 2019, 2020).

Table 2. *Scientific names and numbers of pixels of the training and validation samples for tree species classification*

Tree species number	Scientific names	Training samples	Validation samples
T1	Ginkgo biloba L.	256	1235
T2	Platanus orientalis	261	1285
T3	Platycladus orientalis (L.)	265	1236
T4	Cedrus deodara	260	1248
T5	Paeonia suffruticosa	263	1234
T6	Ligustrum compactum	274	1267
T7	Salix babylonica	268	1271
Grass	—	271	1269

Principal component analysis layer acquisition

Using ENVI 5.4 software, PCA was performed on the WV-2 imagery and the WV-2 imagery with only trees (referred to as WV-2 veg, for consistency, the non-tree/vegetation parts of the WV-2 and WV-3 images are represented as WV-2 veg and WV-3 veg, respectively) retained, resulting in eight PCA layers containing varying amounts of information. As the mask constructed for the WV-3 imagery in previous studies only covered non-vegetation areas, leaving grasses unmasked, the PCA transformation of WV-3 imagery with only vegetation areas retained slightly differs from the WV-2 case (Liu, 2023). The exclusion of non-vegetation areas was primarily achieved through masking, and the method for constructing the mask was detailed in our previous research (Liu, 2023). After the PCA transformation, the cumulative variance of each PCA layer is presented in *Table 3*.

Based on the cumulative variance contribution of the PCA layers (*Table 3*), it can be observed that the first four PCA layers contain almost 99% or more of the information and can effectively represent the entire dataset. The remaining four PCA layers, containing less than 1% of the information, are mainly noise and do not contribute positively to tree species classification. Instead, they increase the complexity of calculations. Therefore, to conduct tree species classification, the latter four PCA layers with less information content were eliminated, and the first four PCA layers with more

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information content were selected. This approach not only retains the layers that ensure an improvement in classification accuracy but also enhances computational efficiency during the classification process.

Table 3. *The cumulative information content of PCA layers extracted from different data and image parts*

PCA layers	WV-2		WV-3	
	WV-2 (%)	WV-2 veg (%)	WV-3 (%)	WV-3 veg (%)
PCA 1	74.01	70.75	62.83	64.50
PCAs 1-2	95.64	96.44	93.41	93.05
PCAs 1-3	98.98	98.66	98.49	97.75
PCAs 1-4	99.49	99.07	99.18	98.69
PCAs 1-5	99.71	99.43	99.55	99.33
PCAs 1-6	99.87	99.74	99.76	99.63
PCAs 1-7	99.95	99.89	99.90	99.84
PCAs 1-8	100.00	100.00	100.00	100.00

Image classification and result evaluation

Given that the PCA dataset containing four layers belongs to a low-dimensional dataset, the choice of MLC and SVM, two classifiers known for their good performance in low-dimensional datasets, was made for identifying tree species. In low-dimensional datasets, MLC exhibits high classification accuracy when the data follows a normal distribution, while SVM achieves good classification performance by identifying the optimal classification hyperplane, even with a limited number of samples, making it suitable for data with low-dimensional feature spaces (Liu and An, 2020). Compared to other classifiers, both methods are better at handling situations with relatively simple feature spaces and typically achieve higher classification accuracy in such scenarios. Once the tree species classification was complete, the evaluation of whether the extraction of principal components for tree species classification necessitates the removal of non-vegetation parts from the image was conducted by comparing the overall accuracy of tree species classification between the datasets of 4 PCAs and 4 PCAs of veg, as well as examining the relationship between different vegetation area ratios and the enhancement in overall accuracy.

Results and discussion

Proportion of non-vegetation parts in the image

The total area of WV-2 and WV-3 images, the area of non-vegetation, and the proportion of non-vegetation area to the total area are shown in *Table 4*.

As shown in *Table 4*, the proportions of non-vegetation areas in the WV-2 and WV-3 images are 70.31% and 53.09%, respectively, both of which are relatively high. This suggests that extracting PCAs based on the entire image or solely on the vegetation part of the image would result in PCA layers with varying degrees of richness in vegetation signals. The two datasets, with different proportions of non-vegetation areas, may exhibit differences in the accuracy of tree species identification after PCA extraction using different methods.

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***Table 4.** Statistical Results of Non-Vegetation Related Metrics in WV-2 and WV-3 Images*

Data type	WV-2	WV-3
Total area	2.45 km^2	0.71 km^2
Non-vegetation area	1.72 km^2	0.38 km^2
Proportion of non-vegetation area	70.31%	53.09%

Overall accuracy of tree species identification

The overall accuracy of tree species identification using PCA layers extracted from the entire WV-2 and WV-3 images as well as from the vegetation parts of the images, is presented in *Table 5*.

***Table 5.** Overall accuracy of tree species identification based on maximum likelihood and support vector machine using PCAs extracted from different forms*

Data type	WV-2		WV-3	
Classifier used	**MLC**	**SVM**	**MLC**	**SVM**
4 PCAs	66.78 %	68.05 %	65.16 %	69.32 %
4 PCAs of veg	68.25 %	68.36 %	66.00 %	68.46 %

As can be seen from *Table 5*, for WV-2, when using 4 PCAs and 4 PCAs of veg for tree species identification, the accuracy of tree species classification using MLC was 66.78% and 68.25%, respectively; while the accuracy using SVM was 68.05% and 68.36%, respectively. For WV-3, when using 4 PCAs and 4 PCAs of veg for tree species identification, the accuracy of tree species classification using MLC was 65.16% and 66.00%, respectively; while the accuracy using SVM was 69.32% and 68.46%, respectively.

It can be observed that when using the MLC classifier, the accuracy of tree species identification based on PCAs extracted from the vegetation portion of the image was higher than that of PCAs extracted from the entire image. For the SVM classifier, in WV-2, the accuracy of tree species identification using 4 PCAs of veg was higher than using 4 PCAs, while in WV-3, the accuracy using 4 PCAs of veg was lower than using 4 PCAs, showing an anomalous situation. Overall, extracting PCAs from the vegetation portion of the image for tree species identification was better than extracting PCAs from the entire image.

Relationship between the proportion of non-vegetation and overall accuracy difference in tree species identification using different forms of PCA extraction

The statistical differences in the overall accuracy of tree species identification based on 4 PCAs and 4 PCAs of veg under different proportions of non-vegetation areas in the images are presented in *Table 6*.

From *Table 6*, it can be observed that for data with a larger proportion of non-vegetation areas (WV-2), the increase in overall accuracy achieved by 4 PCAs of veg compared to 4 PCAs in tree species identification was 1.47% (based on MLC) and 0.31% (based on SVM). For data with a slightly smaller proportion of non-vegetation areas (WV-3), the increase in overall accuracy achieved by 4 PCAs of veg compared to 4 PCAs in tree species identification was 0.94% (based on MLC) and -0.86% (based on SVM).

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Table 6. *The statistical increase in overall accuracy achieved by 4 PCAs of veg compared to 4 PCAs in tree species identification under different proportions of non-vegetation areas, based on MLC and SVM respectively*

Data type	Non-vegetation area proportion	Overall accuracy improved	
		MLC	SVM
WV-2	70.31 %	1.47 %	0.31 %
WV-3	53.09 %	0.94 %	-0.86 %

Based on the statistics, the larger the proportion of non-vegetation areas in the image, the higher the accuracy of tree species identification achieved by 4 PCAs of veg compared to 4 PCAs. This indicates that the proportion of non-vegetation parts in the image needs to be considered in tree species classification. When the proportion is large, it is best to select the vegetation part of the image for PCA transformation when using PCA layers for tree species classification. However, when the proportion of non-vegetation parts is small, it may be acceptable to perform PCA transformation on the entire image.

The layers derived from principal component analysis are pairwise orthogonal. When the imagery contains only vegetation, these orthogonal layers maximize the representation of differences among vegetation. However, when the imagery contains a high proportion of non-vegetation components, the orthogonal layers maximize the representation of differences among all land cover types, but the differences among vegetation may not be as well-represented. Therefore, performing PCA transformation on the entire imagery, including non-vegetation components, cannot achieve recognition accuracy as high as that achieved by applying PCA solely to the vegetation portion for tree species identification.

Improvement of producer and user accuracy

Taking the WV-2 data with the greatest overall accuracy improvement as an example, based on MLC and SVM classifiers, the histograms of producer and user accuracies obtained from tree species classification using 4 PCAs and 4 PCAs of veg are shown in *Figure 2*.

As can be seen from *Figure 2(a)*, for tree species T3, T4, T5, T6, and T7, regardless of using MLC or SVM, the producer's accuracy obtained from tree species classification using 4 PCAs of veg was higher than that based on 4 PCAs. However, for tree species T2, the opposite situation occurred. For tree species T1, the performance of MLC and SVM was inconsistent between 4 PCAs and 4 PCAs of veg. For user accuracy, for tree species T1, T3, and T7, regardless of using MLC or SVM, the user accuracy obtained from tree species classification using 4 PCAs of veg was higher than that based on 4 PCAs. However, for tree species T2, T4, and T5, the opposite situation occurred. For tree species T6, the performance of MLC and SVM was inconsistent between 4 PCAs and 4 PCAs of veg.

In general, the use of 4 PCAs of veg for tree species identification has led to improved producer and user accuracies compared to the use of 4 PCAs. This indicates that, in the context of tree species classification based on remote sensing images with a significant non-vegetation component, if PCA layers are to be utilized, it is advisable to extract them specifically from the vegetated part of the image.

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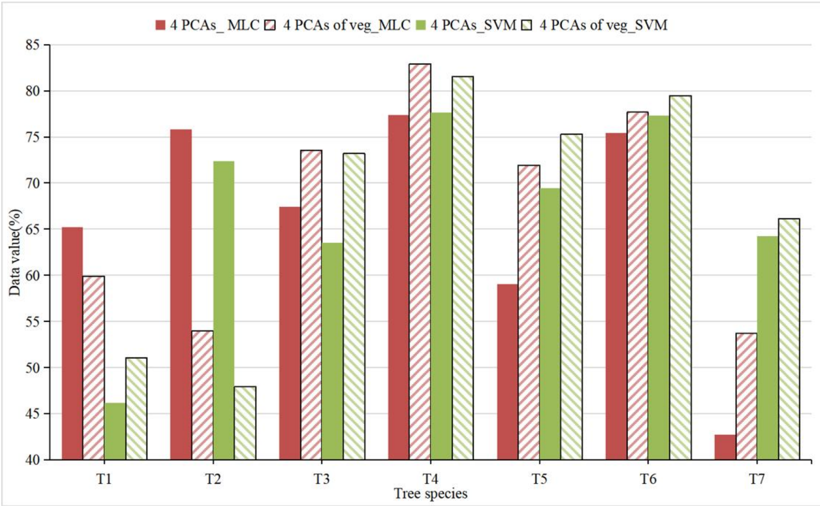
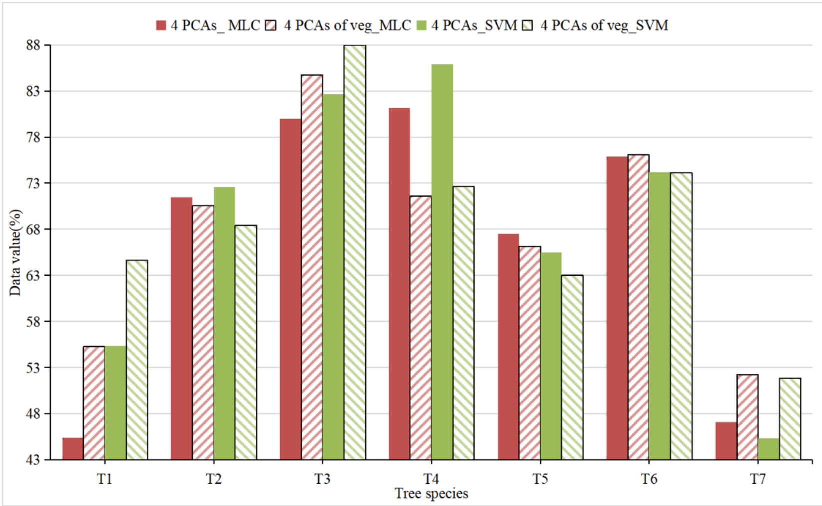


(a)



(b)

Figure 2. *Histograms of producer and user accuracy for tree species classification based on 4 PCAs and 4 PCAs of veg. (a) Producer accuracy histogram; (b) user accuracy histogram*

Maps of tree species classification result

Based on SVM, the use of 4 PCAs of veg from WV-2 and WV-3 has achieved relatively good results in tree species classification. The final classification results obtained from both datasets in tree species classification are shown in *Figure 3*.

Although the main purpose of this study is not to focus on the accuracy of tree species identification based on WV-2 and WV-3, from the classification result maps, it can be seen that T3, T4, T5, and T6 in WV-2 achieved better classification results (*Figure 3(a)*), and T1, T5, and T6 in WV-3 obtained better classification results (*Figure 3(b)*).

The WV-2 and WV-3 datasets exhibited differences in tree species classification performance due to variations in their proportions of non-vegetation areas and spectral characteristics. WV-2, with a higher proportion of non-vegetation areas (70.31%), showed greater accuracy improvement when PCA layers were extracted exclusively from the vegetation portion, highlighting its sensitivity to non-vegetation influences. Conversely, WV-3, with a lower proportion of non-vegetation areas (53.09%), exhibited

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smaller improvements and minor anomalies in SVM results, indicating that its PCA-derived layers were less influenced by non-vegetation components. These findings emphasize the need to tailor PCA strategies to dataset-specific characteristics for achieving optimal classification performance.

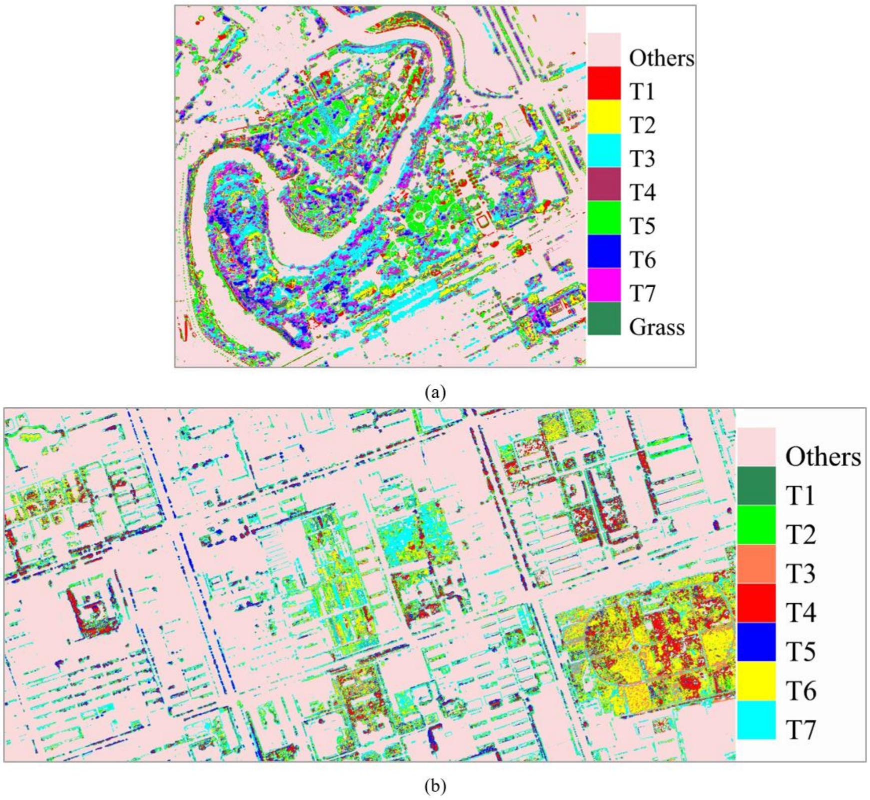

Figure 3. *The result map of tree species classification based on 4 PCAs of veg from WV-2 and WV-3. (a) Based on WV-3 data; (b) based on WV-2 data, the tree species identified based on WV-2 recognition for T1 to T7 differ from those identified using WV-3 recognition for the same T1 to T7*

In this study, we found that using the vegetation component of the imagery for Principal PCA transformation yields higher accuracy in tree species identification compared to using the entire imagery for PCA. In practical applications, especially in tree species identification based on hyperspectral PCA transformation, this strategy can effectively enhance the accuracy of tree species recognition and has positive implications for species identification in ecosystem management using remote sensing.

Conclusions

In order to determine which extraction method—utilizing the entire image or only the vegetation part—performed better when using PCA layers for tree species recognition in images with a certain proportion of non-vegetation components, this study employed WV-2 and WV-3 data and classified tree species using MLC and SVM. The study reached the following conclusions: (1) The layers obtained by PCA transformation using the vegetation part of the image achieved higher overall accuracy for tree species

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classification compared to the layers obtained by PCA transformation using the entire image. (2) The higher the proportion of non-vegetation components in the image, the higher the overall accuracy of tree species recognition obtained by PCA transformation based on the vegetation part of the image compared to PCA transformation based on the entire image. (3) For images with a large proportion of non-vegetation components, it is suitable to select images of the vegetation part for PCA transformation in tree species recognition. In future tree species identification research or practical applications, when both vegetation and non-vegetation parts exist in the imagery, it is recommended to first apply a mask to remove the non-vegetation parts, followed by principal component analysis to obtain feature layers for tree species identification.

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