



Article Fusion of UAV Hyperspectral Imaging and LiDAR for the Early Detection of EAB Stress in Ash and a New EAB Detection Index—NDVI_(776,678)

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Abstract: Beijing's One Million Mu Plain Afforestation Project involves planting large areas with the exotic North American tree species Fraxinus pennsylvanica Marsh (ash). As an exotic tree species, ash is very vulnerable to infestations by the emerald ash borer (EAB), a native Chinese wood borer pest. In the early stage of an EAB infestation, attacked trees show no obvious sign. Once the stand has reached the late damage stage, death occurs rapidly. Therefore, there is a need for efficient early detection methods of EAB stress over large areas. The combination of unmanned aerial vehicle (UAV)-based hyperspectral imaging (HI) with light detection and ranging (LiDAR) is a promising practical approach for monitoring insect disturbance. In this study, we identified the most useful narrow-band spectral HI data and 3D LiDAR data for the early detection of EAB stress in ash. UAV-HI data of different infested stages (healthy, light, moderate and severe) of EAB in the 400-1000 nm range were collected from ash canopies and were processed by Partial Least Squares-Variable Importance in Projection (PLS-VIP) to identify the maximally sensitive bands. Band R678 nm had the highest PLS-VIP scores and the most robust classification ability. We combined this band with band R776 nm to develop an innovative normalized difference vegetation index (NDVI(776,678)) to estimate EAB stress. LiDAR data were used to segment individual trees and supplement the HI data. The new NDVI(776.678) identified different stages of EAB stress, with a producer's accuracy of 90% for healthy trees, 76.25% for light infestation, 58.33% for moderate infestation, and 100% for severe infestation, with an overall accuracy of 82.90% when combined with UAV-HI and LiDAR.

Keywords: EAB; early detection; hyperspectral; LiDAR; vegetation indices

1. Introduction

As an international wood borer pest, the emerald ash borer (EAB) *Agrilus planipennis* Fairmaire seriously endangers imported fast-growing tree species such as the *Fraxinus pennsylvanica* Marsh (ash) in China, and has severely harmed ash since invading North America [1]. In China, largely artificial, single-species stands weaken the forest structure. Several plain afforestation projects have been carried out in Beijing alone since 2010, and the introduction of *F. pennsylvanica* caused a large outbreak of EAB. As a native pest, EAB coevolved with *Fraxinus Chinensis*, which shows strong EAB resistance; the typical population of EAB is very stable and does not cause severe damage. However, with the introduction of weakly EAB-resistant ash, the population of EAB has exploded and killed large areas of artificial ash forests.

New technologies are urgently needed to prevent the further spread of EAB, and timely prevention is critical. *F. pennsylvanica* infested by EAB dies gradually in three to four years [2]. The delayed death of ash to EAB highlights the importance of timely



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Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). prevention. However, such prevention requires an effective method to accurately identify EAB in the early stage of damage [3]. New infestations are difficult to identify with the naked eye [4]. However, various tree symptoms can indicate an infestation, including crown thinning, D-shaped exit holes, distinct S-shaped larval feeding tunnels, and increased woodpecker activity. The chlorophyll content of leaves is also an important indicator of tree stress. As the stress worsens, chlorophyll content gradually decreases. The changes in leaf reflectance caused by stress are directly related to leaf chlorophyll content [5,6]. Efficient field estimates of these chlorophyll-related changes can be obtained from chlorophyll fluorescence measurements, which are indicative of the net photosynthesis of an entire tree [7].

Remote sensing technology is essential for identifying large-scale physiological and morphological changes in trees [8,9]. The studies on the remote sensing of insect disturbances can be grouped into three types: bark beetles, broad-leaved defoliators, and coniferous defoliators. Among them, bark beetles accounts for majority. Moreover, these studies mainly use low and medium resolution data. Random forest is the most widely used classification model for mapping disturbance occurrence [10]. However, traditional RS approaches have several limitations for detecting forest stress. First, forest ecosystems are complex to investigate. Second, it is difficult to capture subtle changes in stressed trees with satellite remote sensing [11]. Murfitt et al. [3] assessed the feasibility of using Worldview-2 images to assess the decline in EAB-infested ash forests. The overall accuracy of this approach for different EAB stress stages was 70%. Unmanned aerial vehicle (UAV) remote sensing enables data acquisition from inaccessible areas and captures subtle changes in the tree canopy after damage [12].

However, no study has yet tested UAV-HI and LiDAR remote sensing for EAB detection, let alone examined the spectral sensitivity of HI and LiDAR to EAB infestations. The early detection of vegetation stress through hyperspectral narrow-band information mainly determines the spectral region that is most sensitive to stress. There are many precedents of applying narrow-band HI data for the early detection of adverse growth conditions. Hoque et al. [13] have reported that narrow wavebands within the 480-680 nm range help to detect adverse growth conditions. Carter [14] found that the reflectance of 690–700 nm strongly correlates with leaf chlorophyll content. Yu et al. [15] indicated that spectral reflectance differences in the 680–760 nm range are most obvious between healthy and infected pines. These results showed that the narrow band around 700 nm can detect plant stress earlier. Based on detailed analysis, the sensitive bands for early stress detection must be determined separately for different tree species. However, spectral reflectance differences are usually too little to identify stressed trees. Vegetation indices are frequently computed using relatively broad spectral bands of airborne and spaceborne sensors. Commonly used vegetation indices such as the normalized difference vegetation index (NDVI) have shown promising results in distinguishing the degree of vegetation damage [16,17]. However, they are usually calculated from wideband satellite remote sensing data. With the development of UAV hyperspectral imaging (UAV-HI), traditional vegetation indices cannot fully use a large amount of narrow-band information in hyperspectral images. A new method is required to fully exploit this complex and expensive type of hyperspectral information, which contains a large amount of redundant data [18]. Identifying new sensitive bands can significantly improve classification accuracy, especially for early detection, while speeding up the analysis and lowering its cost.

LiDAR can accurately collect the three-dimensional information of objects. The rapid development of UAV systems has greatly enhanced the capabilities of LiDAR in forest health monitoring. Lin et al. [9] and Yu et al. [15] combined hyperspectral and LiDAR data to increase accuracy. The most notable contribution of LIDAR is to segment individual trees and extract the location and structural information of each tree to manage forests with precision. In recent years, a combination of HI and LiDAR has been used to study early infestations, although it has not previously been used to study broad-leaved trees. Compared with coniferous trees, broad-leaved trees show more apparent changes in their

three-dimensional structure after damage, potentially making the use of LiDAR more effective. Moreover, early detection at a single-tree scale requires the accurate segmentation of individual trees. Compared with spectral images, LiDAR has shown better accuracy for single-tree segmentation. Various studies have explored the combination of lidar and high-resolution imagery to segment forest stands, extract forest features and assess forest biomass and vigor. Dechesne et al. [19] reported that using lidar and very high-resolution imagery can significantly improve single-wood segmentation. Data collection using lidar and very high-resolution optical images has been proven to help in improving the process of feature extraction [20]. Reyes-Palomeque et al. [21] also confirmed that combining lidar data and airborne imagery of a very high resolution can improve the accuracy of aboveground biomass estimation, particularly in forests with complex vegetation structures. However, the combination of HI and LiDAR has not previously been applied to EAB monitoring. In this study, we investigated how tree stress caused by EAB could be detected using UAV-HI and LiDAR with three specific objectives: (1) determine which narrow-band spectral HI data and 3D LiDAR data are the most beneficial for the early detection of EAB stress in ash; (2) develop an effective and quick method for the early detection of EAB-related stress in F. pennsylvanica combining UAV-HI and LiDAR; and (3) develop a semi-automatic classifier for the early detection of EAB in ash trees in the Beijing region.

2. Materials

2.1. Study Area

The study area $(37.7125^{\circ}N, 116.8528^{\circ}E)$ was an ash tree forest in Huoxian Town, Tongzhou District in Beijing, China (Figure 1). The area size of the study area was 14.6 hectare. The local elevation is 12 m, the annual average precipitation is 580 mm [22], and the average yearly temperature is 18–23 °C [23]. Because of intensive management, ash trees were the only tree species in the study area, and many exhibited different stages of EAB damage. We confirmed that EAB was the major stressor of the ash forest.



Figure 1. EAB research area in Beijing, China. The UAV flight area is marked in yellow, and two sampled plot locations are marked red.

2.2. Ground Truth data Collection

Field investigations were conducted in August and September of 2021, and an area of significant EAB infestation was identified based on extensive inspections. After selecting two suitable field plots of 50 m \times 50 m, 108 ash trees with similar breast height diameters were selected in the field. To determine the damage stages of the sampled trees, we counted the trunk exit holes at the height of 1–2 m, measured chlorophyll fluorescence and leaf area index (LAI), and assessed the extent of woodpecker activity (see Section 2.2.3). The locations of the sampled trees were recorded using a handheld Differential Global Positioning

System instrument (DGPS, Version S760, South Surveying & Mapping Technology Co., Ltd., Guangzhou, China) with sub-meter accuracy.

2.2.1. Chlorophyll Fluorescence

A reduction in net photosynthesis is one of the most significant physiological manifestations of early stress in trees. Dark-adapted leaves can be used for chlorophyll fluorescence measurement to estimate the net photosynthesis of the entire tree [24]. The quantum yield (QY) of photosystem II (PSII) [25] was used as a representative index of chlorophyll fluorescence. We measured QY with a FluorPen FP100 (Photon Systems Instruments, Brno, Czech Republic) [26]. Before measurement, the intensity of the super pulse was set to 80% and the intensity of the flash pulse was increased for samples with very low chlorophyll density.

2.2.2. Crown Thinning

Crown thinning is the most critical visual feature of ash decline (Figure 2b) [27]. We measured leaf area index (LAI) to assess the crown thinning of each sampled tree. LAI represents leaf density and reflects biophysical abilities such as photosynthesis and the respiration of trees [28]. We calculated the tree LAI by averaging four individual measurements taken in the cardinal directions by a LAISmart [29].



Figure 2. (a) Images of a healthy tree; (b) images of crown thinning; (c) D-shaped exit holes and woodpecker activity.

2.2.3. D-Shaped Exit Holes and Woodpecker Pecking Holes

D-shaped exit holes produced by EAB adults are the most intuitive features of EAB damage [30]. We counted the EAB exit holes on the main bole at 1–2 m above the ground to assess the degree of EAB damage. Traces of woodpecker activity are also critical for determining EAB damage. Woodpecker feeding holes were counted to evaluate the degree of EAB damage. Exit holes and woodpecker feeding holes can be seen in Figure 2c.

2.2.4. Canopy Color

Canopy RGB images of each inspected ash tree were shot with a Yu Mavic2 Professional UAV (DJI, Shenzhen, China). We used the UAV images and the tree position point of DGPS to visually distinguish the canopy color of the sample ash trees.

2.2.5. UAV-Based Hyperspectral Imagery and LiDAR Acquisition

HI and LiDAR data were acquired by a DJI Matrice 600 (DJI, Shenzhen, China) UAVmounted system (IRIS Inc., Shanghai, China) (Figure 3). HI data were collected with a Pika L hyperspectral camera (Resonon, Bozeman, MT, USA). LiDAR data were acquired simultaneously using an LR1601-IRIS (IRIS Inc., Shanghai, China). We mounted both the hyperspectral camera and the LiDAR on the UAV and obtained spectral and LiDAR data during the same flight campaign.



Figure 3. The UAV-mounted system with LR1601-IRIS LiDAR and Pika L imaging spectrometer.

HI data were collected for 30 min (12:40–13:10) on 1 September 2021. The flight height was 120 m, and the front and side overlaps were 60%. The field of view angle was 17.6°, and the focal length was 17 mm. The HI included one hundred and fifty spectral channels with a 5 cm spatial resolution from the visible to the near-infrared regions (400–1000 nm). Reflectance correction and radiometric calibration were performed using a 3 m² carpet reference and Spectronon software (Resonon, Bozeman, MT, USA). Image geometric corrections were performed using eight ground control points (GCPs) recorded using a DGPS device with sub-meter accuracy.

The LiDAR pulse repetition frequency was 5–20 Hz; laser wavelength was 905 nm; and there were 2 returns per pulse. The point density ranged from 100 to 900 points per m². We georeferenced the LiDAR data in the Universal Transverse Mercator (UTM) 51 N and took the WGS1984 datum as the coordinate system.

3. Methods

3.1. Individual Tree Decline Ratings

Figure 4 shows the general workflow of the experiment. To minimize the subjective error of evaluating a single physiological parameter, we standardized and integrated four individual tree parameters into a single decline rating to characterize the degree of ash damage under EAB stress and explore its relationship to the canopy spectral response. We implemented the following steps regarding a previous study by Pontius et al. [31].

First, we standardized individual tree parameters with different numerical ranges into the same quantitative range. A four-level quantile distribution analysis (healthy through severe) was performed for each parameter to convert the original data into 1–4 levels, in which 4 represented a healthy tree and 1 represented a tree that was seriously damaged and on the verge of death (Table 1).



Figure 4. The general workflow of the experiment.

Table 1. Quantile cut-offs for the continuous variables used to calculate decline ratings.

Decline Ratings Quantile	Measured QY LA		Number of Exit Holes	Number of Woodpecker Feeding Holes		
4	0.606-0.85	2.88-4.51	0–4	0–3		
3	0.493-0.605	2.11-2.87	5-10	4–9		
2	0.158-0.492	1.62-2.10	11–18	10–16		
1	0-0.157	0–1.61	19–31	17–32		

We then averaged the four standardized values per tree to obtain a single, comprehensive tree decline rating, representing the combined values of the four measured tree parameters: QY, LAI, number of exit holes, and number of woodpecker feeding holes. Because these averaged tree ratings were not always integers, we again standardized these values to determine ranges associated with the four stages of tree decline from healthy to heavy infestation (Table 2). Finally, 80 of the 108 canopy-dominant ashes were clearly displayed with their decline ratings (Healthy: 23; Light: 22; Moderate: 15; Severe: 20).

Damage Stage	Average Tree Decline Rating Value		
Healthy (H)	3.17–4		
Light (L)	2.39-3.16		
Moderate (M)	1.39–2.38		
Severe (S)	1–1.38		

Table 2. Tree decline ratings associated with four stages of EAB damage in ash trees.

3.2. Individual Tree Segmentation and Feature Extraction

LiDAR is widely used to segment individual trees with high accuracy. Here, a canopy height model (CHM) segmentation algorithm separated the tree crowns in the LiDAR360 software (GreenValley Inc., Shanghai, China) [32]. The improved progressive TIN densification (IPTD) algorithm was used to classify the raw LiDAR point data into the ground and aboveground points using LiDAR360 software. The 0.5 m raster products, including the digital elevation model (DEM), digital surface model (DSM), and canopy height model (CHM), were derived from the classified point cloud. Based on the CHM segmentation result, the tree locations, tree heights, crown diameters, and crown areas were extracted. [33].

Under dense forest conditions in our sample sites, LiDAR cannot distinguish each tree exactly [14]. We manually delineated missing trees by comparing the LiDAR segmentation results with field investigations (Figure 5). The UAV-HI narrow-band reflectance and LiDAR metrics were then extracted at a single-tree scale.



Figure 5. (a) Original LiDAR image of a sample plot; (b) crown segmentation by the CHM algorithm based on LiDAR data. The black circles represent correctly segmented crowns; the red circles represent the manually defined crowns.

3.3. Separation of Raw Hyperspectral Bands

Spectral values were extracted from the UAV-HI data for ash trees with different degrees of damage, as described in Section 3.1. Raw reflectance data were first smoothed with a Savitzky–Golay filter [34] by first-order polynomial. In total, we analyzed 150 bands from 400 to 1000 nm. Partial Least Squares–Variable Importance in Projection (PLS-VIP) [35] was performed to explore the sensitivity of the hyperspectral data to different stages of ash damage. Outliers were identified using the VIP score. A higher VIP score implies that a given band is more sensitive to EAB stress [36]. VIP scores > 0.95 were considered classification-sensitive bands (Figure 6). Five band ranges of 484–500 nm, 521–571 nm, 608–698 nm, 720–741 nm, and 938–1000 nm were calculated as sensitive band ranges with VIP scores > 0.95. Then, we selected the highest VIP score band in each sensitive band range for use in classification. Our data indicated that R678 nm responded most consistently to EAB stress, and four additional sub-maxima from sensitive band ranges (R496, R546, R720 and R988) were also selected for classification. The classification process was performed using the "random Forest" R package [37]. The training and validation data were set at a 7:3 ratio. Ten-fold cross-validation was used to assess model accuracy [38]. The importance

of each variable was determined by the mean decrease accuracy (MDA) value. In the random forest (RF) algorithm, the MDA value of each variable is measured by comparing how much the out-of-bag (OOB) error of the estimate increases when it is excluded and the other variables are left unchanged. The higher the MDA value of a variable, the greater its importance is [39].



Figure 6. VIP scores of 150 HI raw bands, points above the imaginary line mean VIP score > 0.95. Each blue dots means a HI raw bands.

3.4. Ratio and Normalized Analysis of Sensitive Bands

As shown in Figure 7, the producer's accuracy for light infestation using five pieces of original hyperspectral band data was only 48.75%, much lower than required for the early monitoring of pest damage. The further mining of single-band information is needed for the early detection of EAB stress. The band with the strongest and weakest sensitivity to stress can be selected for ratio analysis [40]. When the band most sensitive to stress is analyzed as the numerator or denominator, the resulting ratio for a stressed canopy is more significant than that of a healthy canopy. Thus, reflectance differences and sensitivity maxima used in the ratio analyses were identified in Section 3.3. The band with the highest VIP score, 678 nm, also obtained the highest MDA in RF, defined as a maximally sensitive band (Figure 8). The bands with minimum sensitivity were selected from the remaining bands with VIP scores < 0.95. Finally, the 776 nm and 678 nm ratio was obtained with a constant index value for four different damaged ash trees (Figure 9).

	Health	Light	Moderate	UA(%)			
Health	7.8	1.8	0.2	0	79.59		
Light	1.2	3.9	2.5	0	51.31		
Moderate	0	2.2	3.3	1.2	49.25		
Severe	0	1	0	6.8	98.55		
	86.67	48.75	55.00	85.00 PA(%)			
OA: 70.32%							

Figure 7. Confusion matrices for four infection stages applying selected raw HI bands based on RF classification. The color depth represents the size of the value.



Figure 8. Mean decrease accuracy values of selected raw HI bands based on RF classification. The red box indicates the maximum MDA value.



Figure 9. Under the 95% confidence interval: (**a**) ratio_(776,678) value corresponding to different damaged stages; (**b**) NDVI_(776,678) value corresponding to different damaged stages; Dots represents outliers. H—Health; L—Light; M—Moderate; S—Severe.

To increase the sensitivity of the ratio of the 776 nm and 678 nm wavelengths to changes in the ash forest, it was normalized to the range of [0, 1], similarly to the principle of the NDVI [41]. Thus, a new NDVI based on narrow-band reflectance NDVI_(776,678) was calculated, as shown in Equation (1):

$$NDVI_{(776,678)} = \frac{R776 - R678}{R776 + R678}$$
(1)

where R776 refers to the reflectance at 776 nm and R678 refers to the reflectance at 678 nm.

3.5. Comparison with Other Vegetation Indices

A series of VI indices and LiDAR metrics were also calculated [9,41–44]. Before selecting a variable set to be applied to predicting EAB stress, stepwise regression with a 95% confidence level was used to eliminate multicollinearity between variables. Finally,

21 variables were selected for tree damage estimation, including 11 VIs (Table 3) and 10 LiDAR metrics (Table 4). The Student's *t*-test and RF classification were used for the separability and accuracy comparison of $NDVI_{(776,678)}$ among these variables. The Student's *t*-test was used to check the significance of the VIs and LiDAR metrics difference of healthy (H), lightly (L), and moderately (M) infested stages to verify their sensitivity to the light stage for the objective of early detection.

Table 3. List of hyperspectral variables.

Variables	Formula	Reference
CSC	R605/R760	[42]
GI	R554/R677	[45]
NPQI	(R415 - R435)/(R415 + R435)	[46]
GMB	R750/R700	[43]
WBI	R970/R900	[47]
ACH	SUM(R600:R700)/SUM(R500:R600)	[48]
NWI	(R970 - R850)/(R970 + R850)	[49]
Cse	R605/R760	[42]
NDVI	(R800 - R670)/(R800 + R670)	[41]
NDVI _(810.450)	(R810 - R450)/(R810 + R450)	[50]
Range (690, 740)	MAX(R690:R740) - MIN(R690:R740)	[51]

Table 4. List of LIDAR metrics.

Metrics	Definition
CC	Canopy cover
GF	Gap fraction
AIH_99th	Accumulate interquartile height of 99th
AIH_95th	Accumulate interquartile height of 95th
AIH_kurtosis	Kurtosis of accumulate interquartile height
AIH_max	Maximum point cloud height
AIH_min	Maximum point cloud height
Int_p90	90th percentile of crown return intensity
Int_p95	95th percentile of crown return intensity
Int_p99	99th percentile of crown return intensity

RF classification was used to test the classification accuracy and the contribution of NDVI_(776,678). Six models were used for RF, each of which used a different set of data: (1) Model A included NDVI_(776,678), other vegetation indices, and LiDAR metrics; (2) Model B included NDVI_(776,678) and other vegetation indices; (3) Model C included NDVI_(776,678) and LiDAR metrics; (4) Model D included other vegetation indices and LiDAR metrics; (5) Model E included only the other vegetation indices; and (6) Model F included only the LiDAR metrics.

4. Results

4.1. EAB-Sensitive Bands of Hyperspectral Image

The average reflectance curves (400–1000 nm) for the four EAB infestation stages of ash are depicted in Figure 10. The band ranges with PLS-VIP scores > 0.95 for classification were 484–500 nm, 521–571 nm, 608–698 nm, 720–741 nm, and 938–1000 nm. The single band with the highest PLS-VIP score for classification was 678 nm at the red edge. The single bands with the highest PLS-VIP scores in each sensitive band range were 496 nm in 484–500 nm, 546 nm in 521–571 nm, 678 nm in 608–698 nm, 720 nm in 720–741 nm, and 988 nm in 938–1000 nm.



Figure 10. Mean reflectance values of the ash canopy at different stages of EAB damage in selected sensitive band ranges: (a) 400–1000 nm; (b) 484–571 nm; (c) 608–698 nm; (d) 938–1000 nm.

4.2. Comparison of NDVI(776,678) with Existing Vegetation Indices and LiDAR Metrics

The statistically significant difference of NDVI(776,678), eleven VI values, and ten LI-DAR metrics between the healthy (H), lightly (L), and moderately (M) damaged ash trees are depicted in Figures A1 and A2. NDVI(776,678) was statistically significantly different (p < 0.0001) in healthy (H), lightly (L), and moderately (M) damaged ash trees. Table 5 shows the RF classification results for the four stages of EAB damage obtained using six sets of variables. Models that included NDVI(776,678) had greater classification accuracy than those that excluded NDVI(776,678). Model A (NDVI(776,678), other vegetation indices, and LiDAR metrics) had a higher classification accuracy for each damage stage than the other four models. For Model A and Model D containing both HI and LiDAR, Model A had a higher OA (82.90%) than Model D (79.68%). Their producer's accuracies were 90% versus 91.11% at the healthy stage; 76.25% versus 61.25% at the light stage; and 58.33% versus 61.54% at the moderate stage. For Model B and Model E, which contained only HI, Model B had a higher OA (79.03%) than Model D (75.97%). Their producer's accuracies were 87.78% versus 87.78% at the healthy stage; 68.92% versus 52.50% at the light stage; and 53.03% versus 56.90% at the moderate stage. The incorporation of NDVI(776.678) greatly improved classification accuracy for the light stage, increasing it from 34.48% in Model F to 60.00% in Model C, from 52.5% in Model E to 68.92% in Model B, and from 61.25% in Model D to 76.25% in Model A. These results demonstrate that NDVI(776,678) shows high sensitivity for the light stage of EAB damage in ash, which meets the objectives of the early detection of EAB stress in F. pennsylvanica. When LiDAR data were used alone for classification, the accuracy was only 50%, but when LiDAR data were used to supplement the HI information, they significantly improved the classification accuracy. Figure 11 shows the confusion matrices of Model A among 22 variables (containing NDVI(776.678), 11 other vegetation indices, and 10 LiDAR metrics) based on RF classification. Figure 12 shows Model A's top 10 mean decrease accuracy values among 22 variables. NDVI(776.678) had the most significant importance of all the parameters.

Model		Healthy Lightly		Moderately		Severely		All Stages		
		UA (%)	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	OA (%)
Include NDVI _(776,678)	HI + LIDAR HI LIDAR	86.17 84.04 82.22	90.00 87.78 68.51	64.89 56.67 48.00	76.25 68.92 60.00	83.33 76.09 46.42	58.33 53.03 43.33	100 100 74.47	100 100 72.92	82.90 79.03 70.32
Exclude NDVI _(776,678)	HI + LIDAR HI LIDAR	81.19 75.24 66.67	91.11 87.78 83.33	59.76 53.83 30.56	61.25 52.50 34.38	76.92 73.33 30.00	61.54 56.90 12.50	100 100 54.55	100 100 56.25	79.68 75.97 50.00

Table 5. RF classification results of four EAB damage degrees by six datasets.



Figure 11. Confusion matrices of Model A among 22 variables (containing NDVI_(776,678), 11 other vegetation indices and 10 LIDAR metrics) based on RF classification. The color depth represents the size of the value.



Figure 12. Top 10 mean decrease accuracy values of Model A among 22 variables (containing NDVI_(776,678), 11 other vegetation indices and 10 LIDAR metrics). The red box indicates the maximum MDA value.

4.3. Relationship between Canopy Color and Tree Damage

A change in canopy color reflects the gradual progression of EAB damage in individual ash trees. Four different canopy colors (green, yellowish, yellow and red) indicate the progression from healthy to damaged to dying under EAB stress. Clear thresholds in the four tree parameters between the colors with 95% confidence intervals can be observed in Figure 13. QY and LAI decreased as the canopy color changed from green to yellowish to yellow to red. The number of D-shaped holes and woodpecker pecking holes increased as the canopy color changed. As such, canopy color extracted from an orthographic image is closely related to the physiology of the tree and is an excellent indicator of EAB stress.



Figure 13. Differences in four physiological factors and four canopy colors with 95% confidence intervals. (a) QY; (b) LAI; (c) Exit hole number; (d) Woodpecker pecking holes. Dots represents outliers.

4.4. Tree Damage Mapping

Figure 14 shows the mapping results of different EAB stress stages in ash throughout the UAV flight area. The RF algorithm containing NDVI_(776,678), 11 other vegetation indices and 10 LiDAR metrics was used to map the EAB stress on ash. The locations and crown diameters of the ashes were tagged by the segmentation results of LiDAR data.



Figure 14. (a) HI in the flight area. (b) EAB stress mapping containing NDVI_(776,678), 11 other vegetation indices and 10 LiDAR metrics by RF in the research plot.

5. Discussion

5.1. Remote Sensing Monitoring Window for Broad-Leaved Trees

Monitoring wood borer pest damage by remote sensing has more limitations in broadleaved trees than in conifers. Nevertheless, the enormous economic and ecological losses caused by borer pests to broad-leaved trees are no less than conifers. This is because broad-leaved deciduous tree canopies gradually decline with the onset of cool weather in the autumn, even if they are not affected by borer pests. Thus, an appropriate monitoring period for the remote sensing of broad-leaved trees must be selected to minimize the effect of phenology. The best monitoring window for broad-leaved trees differs depending on the region, particularly along a north-south gradient, and the specific phenological conditions will influence it in a given region. Local management data can obtain the deciduous period of broad-leaved trees within a particular area. Although the impact of phenology is vast, it can nonetheless be avoided. Phenological phenomena do not affect broad-leaved trees throughout the year, but only when the weather becomes cool in autumn. Moreover, phenological phenomena affect all stands in a region, not specific trees. Early changes in canopy color that occur well before natural defoliation are typically caused by diseases and pests. This theoretical basis permits us to use remote sensing to monitor the diseases and pests of broad-leaved trees. In Beijing, leaf fall in broad-leaved trees generally occurs in late October. The period for the remote sensing of broad-leaved trees for pest and disease monitoring is short compared with conifers. The optimal time occurs after the peak spring and before fall defoliation. Throughout the yearly growth cycle, a time-series study will be required to determine the best monitoring window for distinguishing different EAB damage stages in ash. This will be the focus of our next project.

5.2. Ash Canopy Color and Damage Stages

Canopy color has not previously been applied for EAB detection. Based on the characteristics of borer pest damage and the responses of broad-leaved trees, we speculated that ash trees would also show different canopy colors under various degrees of EAB damage. Our field inspections indicated that the canopy color of ash trees under EAB stress changed gradually from green to red before tree death. A clear relationship was observed between canopy color and EAB damage stages, highlighting the value of canopy color as a damage assessment parameter. By determining the canopy color of ash trees with different degrees of EAB damage, we can visually identify EAB stress in ash trees through orthophoto remote sensing images, as can be performed for conifers.

5.3. Method for the Early Detection of EAB

Here, we determined that the 678 nm band had the most robust classification ability for EAB damage and developed a new vegetation index, NDVI_(776,678), which showed stable performance in the early detection of EAB damage. As shown in Table 5, the classification accuracies of the light stage using NDVI_(776,678) were higher than those not using NDVI_(776,678). This result indicates that NDVI_(776,678) has a high sensitivity to EAB damage in ash. By applying the new narrow waveband index, it is possible to detect EAB damage to ash earlier. Therefore, NDVI_(776,678) can be used for the early monitoring of ash damage in precision forestry.

The classification accuracy for the severe stage was 100%. The accurate detection of severely infested trees is essential for controlling an EAB outbreak. It is challenging to save a severely infected tree using physical and chemical approaches, but timely detection can save nearby ash trees from EAB damage. Although a severely infested ash tree will typically die the following year and is beyond treatment, large numbers of larvae are overwinter in its trunk. Timely removal will prevent these trees from becoming infestation hot spots from which EAB can invade surrounding trees in the next growing season.

Compared with HI, LiDAR's ability to classify the damage degree of ash trees is very weak. This is because the narrow band information of hyperspectral images strongly correlates with the physiological state of plants but not LiDAR signal. [52]. Hence, early monitoring using LiDAR alone is challenging. Using lidar sensors with higher point cloud density may improve the detection of crown thinning in infested trees. The point density of the LiDAR used in this study ranged only from 100 to 900 points per m², likely explaining its poor performance. Lidar can be used for single-wood segmentation and the acquisition of three-dimensional structures. The addition of LiDAR data also improved classification accuracy combined with HI.

Identifying pest-sensitive UAV-HI bands is of great significance to the remote sensing monitoring of borer pests. For practical applications, the narrow-band spectral information of UAV-HI is essential for pest stress detection. However, the method contains a large amount of redundant data, which increases the difficulty of data processing and the cost of acquisition. Replacing the full-band acquisition with fewer but stress-sensitive bands could speed up the analysis while costing less money. Further research of sensitive bands could significantly improve classification accuracy, especially for early detection.

6. Conclusions

The precision management of the borer pests of broad-leaved trees is an integral part of sustainable forest management. Because of the complexity of borer pest management, high-tech means are needed for efficient and accurate management. The combination of UAV hyperspectral, lidar, and artificial intelligence technology is an innovative attempt to provide efficient solutions for precision forestry. This study collected narrow-band spectral information from HI and 3D data from LiDAR and developed a new vegetation index, NDVI_(776,678), for the precision management of EAB stress in ash. Within the raw narrowband reflectance spectrum of HI, reflectance at 678 nm proved to be the most sensitive band for detecting EAB stress in ash. LiDAR was successfully used for individual tree segmentation. The accuracy of LiDAR data alone for distinguishing damage stages in ash trees was very low, showing that LiDAR is not sensitive to the early detection of EAB stress in *F. pennsylvanica*.

The new index, NDVI_(776,678), was statistically significantly different (p < 0.0001) between the healthy-, light-, and moderate-stage ash trees. Meanwhile, it identified EAB stress stages with an accuracy of 76.25% for the light stage of EAB stress and an overall accuracy of 82.90% for all damage stages when combined with HI and LIDAR, which were higher than those without NDVI_(776,678).

Therefore, NDVI_(776,678) is an excellent new narrow-waveband vegetation index that can be used for mapping different EAB infestation stages in *F. pennsylvanica* and can be used to guide broad-leaved tree health monitoring with remote sensing in Beijing.

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Figure A1. Comparison of the proposed vegetation index $NDVI_{(776,678)}$ with other eleven vegetation indices based on the statistically significant differences of VIs values of Healthy (H), Lightly (L), and Moderately (M) damaged trees at the significant levels of 0.01 (**), 0.001 (***), 0.0001 (****), respectively. "ns" means no significant difference. Dark points in each bar correspond to the distributions of Vi values.



Figure A2. Comparison of the proposed vegetation index NDVI_(776,678) with ten LIDAR metrics based on the statistically significant differences of VIs values of Healthy (H), Lightly (L), and Moderately (M) damaged trees at the significant levels of 0.01 (**), 0.001 (***), 0.0001 (****), respectively. "ns" means no significant difference. Dark points in each bar indicate the distribution of the values of each parameter.

Appendix A

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