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SPECTRAL REFLECTANCE AND VEGETATION INDEX CHANGES IN DECIDUOUS FOREST FOLIAGE FOLLOWING TREE REMOVAL: POTENTIAL FOR DEFORESTATION MONITORING

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It is important to detect and quantify deforestation to guide strategic decisions regarding environment, socioeconomic development, and climate change. In the present study, we conducted a field experiment to examine spectral reflectance and vegetation index changes in poplar and locust tree foliage with different leaf area indices over the course of three sunny days, following tree removal from the canopy. The spectral reflectance of foliage from harvested trees was measured using an ASD FieldSpec Pro spectroradiometer; synchronous meteorological data were also obtained. We found that reflectance in short-wave infrared and red-edge reflectance was more time sensitive after tree removal than reflectance in other spectral regions, and that the normalized difference water index (NDWI) and the red-edge chlorophyll index (CI_{RE}) were the preferred indicators of these changes from several indices evaluated. Synthesized meteorological environments were found to influence water and chlorophyll contents after tree removal, and this subsequently changed the spectral canopy reflectance. Our results indicate the potential for such tree removal to be detected with NDWI or CI_{RE} from the second day of a deforestation event.

Keywords: *deforestation, remote sensing, detection, temporal analysis, reflectance, vegetation index.*

Introduction. Forests play an important role in the global carbon cycle. The total carbon storage of the earth's forests is greater than that of the entire atmosphere [1]. According to the Global Forest Resources Assessment of 2010, forests account for 31% of the world's total land area. However, large areas of forest have been lost mainly because of deforestation [2–4], which impacts local socioeconomic development and global climate change [5] and causes wide scientific concern, especially in tropical region [6–8], while large areas of deciduous forests in temperate zones have also been either cleared for agriculture or destroyed through various other human activities [9–11]. It is therefore important to quantify and monitor deforestation in deciduous forests to help guide strategic decisions regarding global climate change and regional economic development.

Deforestation can be monitored using traditional field-based forest inventory techniques and the capture of deforestation patterns by statistical sampling designs [12]. However, many traditional methods are time-consuming and do not yield results in a timely manner [13]. Remote sensing is widely used to detect and assess forest changes at various spatiotemporal scales. The MODIS instrument onboard the Aqua and Terra satellite platforms has acquired near-daily data that have been particularly beneficial, especially for large regional detection and monitoring [14, 15]. Several methods have been developed using satellite images to detect and monitor deforestation, including visual interpretation, pixel- or object-based methods, pattern decomposition coefficients, and vegetation index changes [13, 16–20]. However, few studies have focused on comparing vegetation spectral variables to identify which variables have a higher relative sensitivity for detecting deforestation.

In the present study, two types of deciduous forest, poplar (*Populus lasiocarpa*) and locust (*Gleditsia triacanthos*), which are deciduous forest and widely distributed in temperate zones, were investigated using field-based spectroradiometers. We aimed primarily to examine spectral reflectance and vegetation index changes in foliage from harvested trees, and to thus

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identify the best indicators for detecting foliage changes and their potential for monitoring deforestation. In the study region described below, trees are generally selectively harvested or clear-cut and then left on the ground for several days. As their foliage senesces, its spectral reflectance changes, thus influencing the radiance detected by a remote sensor. This study was designed to evaluate the temporal dynamics of foliage spectral reflectance during this senescence period to determine when significant reflectance changes occur that may impact the detected radiance from an airborne or satellite sensor.

Methods. *Acquisition of harvested tree foliage spectra.* Trees were harvested from Jia County, Shangxi Province (38.295^{o}N, 110.219^{o}E) at 9:00 a.m. on May 25, 2011; 14 poplar trees and 13 locust trees with different diameters at breast height were harvested. For both species, five sets of typical fresh branch samples were collected from the harvested trees and placed on barren ground in a plot approximately 2 × 2 m in size. We measured the leaf area index (LAI) for each sample and obtained the results of 1.5, 2.5, 4.5, 7.0, and 10.0 using a SunScan canopy analysis system. The spectral reflectance signatures of the harvested tree foliage were measured by an ASD FieldSpec Pro spectroradiometer at 10 nm spectral resolution, over a wavelength range of 350–2,500 nm. Each set of reflectance measurements consisted of five branch samples with ten replicate readings and a white reference Spectralon panel reading. We calculated reflectance by the ratio of spectral radiance reflected by foliage to spectral radiance reflected by the reference panel. Simultaneously, we measured the concentrations of leaf chlorophyll for each sample using a SPAD-502 meter with ten replicate readings. We also measured several meteorological parameters (including mean wind speed, air temperature, relative humidity, heat stress index, and dew point) using a portable Kestrel 3000. The time interval for each measurement sequence was approximately 1 h, with a total of 25 sets of observations collected over three clear and sunny days (May 25–27, 2011) for each of the harvested samples of poplar and locust tree foliage. In the first two days, we missed the observations at 9:00 and 13:00 due to the influence of dew and heavy cloud shadow, respectively.

Analysis of spectral reflectance and vegetation indices. To assess how well broadband sensors (e.g., MODIS) can detect foliage changes and their potential for monitoring deforestation, the above-mentioned spectral reflectance curves were convolved into MODIS wavebands using the spectral response functions of MODIS bands 1–7 (band 1, 620–670 nm; band 2, 841–876 nm; band 3, 459–479 nm; band 4, 545–565 nm; band 5, 1230–1250 nm; band 6, 1628–1652 nm; and band 7, 2105–2155 nm). Vegetation indices (VIs) are commonly used in vegetation canopy studies because of their relative simplicity and robustness [21]. Structural VIs often rely on some combination of near-infrared (NIR) to red reflectance, because increases in LAI result in decreasing red and increasing NIR reflectance. Biochemical and stress-related indices change the absorbing wavelength based on biochemical parameters [22]. Widely used structural indices include the normalized difference vegetation index (NDVI) [23] and the enhanced vegetation index (EVI) [24]. Biochemistry and plant physiology/stress properties include water, chlorophyll, and fluorescence, and their common VIs include the normalized difference water index (NDWI) [25], the simple ratio water index (SRWI) [26], the red-edge chlorophyll index (CI_{RE}) [27], and the photochemical reflectance index (PRI) [28]. Tree removal alters vegetation properties, including vegetation structure, biochemistry, and plant physiology/stress. Thus, based on the VI categories introduced by Thenkabail et al. [22], we selected several typical VIs (Table 1) to assess the applicability of foliage spectral change detection following harvest and the potential of different indices for monitoring deforestation.

The MODIS sensor has two NIR bands (bands 2 and 5) and two SWIR bands (bands 6 and 7). There are thus two, two, four, four, and two possible combinations for calculation of NDVI, EVI, NDWI, SRWI, and CI_{RE}, respectively. Measured spectral reflectance was used to calculate all possible combinations of vegetation indices according to their respective equations (Table 1). Red edge refers to the region of rapid change in reflectance of vegetation, characterized by a maximum slope in the wavelengths between 680 and 740 nm [22]. Thus, we obtained the reflectance in red-edge position derived from the greatest first-order derivative spectrum (R_{RE}) [22]. PRI was calculated using measured spectral reflectance at 531 and 570 nm.

Analysis of harvested tree foliage spectral reflectance and vegetation index dynamics. Spectral reflectance was found to vary in an almost identical manner throughout the whole band range and measurement period (May 25–27, 2011) after tree removal regardless of LAI values. Spectral reflectance and vegetation indices of harvested foliage at different LAI values were therefore averaged for each of the poplar and locust samples for subsequent analysis.

We used coefficient of variation (CV) to evaluate temporal variations in spectral variables across the three-day period. CV is defined as the ratio of standard deviation (S) to mean value ($\overline{X}$) over the time since the trees were harvested, as shown in the following equation:

$$\mathrm{CV} = S/\overline{X} .$$

TABLE 1. Selected Spectral Indices Used to Assess the Applicability of Foliage Spectral Changes Detection and the Potential for Monitoring Deforestation

Categorized Index		Reference
Structure	NDVI = $(R_{NIR} - R_{red})/(R_{NIR} + R_{red})$	[23]
	EVI = $2.5(R_{NIR} - R_{red})/(R_{NIR} + 6R_{red} - 7.5R_{blu} + 1)$	[24]
Water	NDWI = $(R_{NIR} - R_{SWIR})/(R_{NIR} + R_{SWIR})$	[25]
Chlorophyll	SRWI = R_{NIR}/R_{SWIR}	[26]
Light use efficiency	$CI_{RE} = R_{NIR}/R_{RE} - 1$	[27]
	PRI = $(R_{531} - R_{570})/ (R_{531} + R_{570})$	[28]

The CVs of all possible combined vegetation indices were compared, and it was found that The CV of NDVI calculated by MODIS bands 1 and 2 was larger than that of NDVI calculated by MODIS bands 1 and 5. Furthermore, The CVs of EVI (bands 1, 2, and 3), NDWI (bands 2 and 6), SRWI (bands 2 and 7), and CI_{RE} (band 5) were found to be larger than those of other corresponding possible combinations. The same results were observed for both poplar and locust trees. Those VIs with the larger CVs were selected for further analysis regarding their variations with time after tree removal.

In addition, based on 25 observations obtained over three days, we calculated the correlation coefficients between foliage spectral variables and synchronously observed meteorological data to assess the meteorological effects on the speed of changes in reflectance and VIs of harvested tree foliage.

Results and Discussion. *Variation in spectral reflectance with time after tree removal.* Figure 1a shows variations in the spectral reflectance of harvested poplar foliage, represented through MODIS bands 1–7 from May 25–27, 2011. Maximum reflectance was observed at the end of each day during the first two days after tree removal, and also at 13:00 on May 27. A general overall increase in reflectance with time was found throughout MODIS bands 1–7. Based on CV values, reflectance in MODIS band 7 (SWIR) exhibited the most significant increase (from 0.09 to 0.28) with a CV of 0.28, followed by MODIS band 6 (SWIR) where reflectance increased from 0.23 to 0.49 with a CV of 0.22. Smaller increases were also found in MODIS bands 1 (red), 3 (blue), 5 (NIR), and band 4 (green), in descending order. Both variations in spectral reflectance and in CVs of deforested locust tree foliage were in complete agreement with those of harvested poplar tree foliage throughout MODIS bands 1–7 (Fig. 1b).

On the second day following tree removal, the red-edge position of the harvested poplar foliage exhibited a very significant "blue shift", and was moved from 724 to 702 nm for poplar trees and from 730 to 719 nm for locust trees (Fig. 2a). The reflectance in the red-edge position decreased sharply on the second day following tree removal (Fig. 2b). These results indicated that the red-edge position and reflectance of foliage from harvested trees were very sensitive to time, and that tree removal could be detected from the second day following harvest.

Variation in vegetation indices with time after tree removal. Harvested poplar foliage vegetation indices were normalized with their temporal variations after tree removal (Fig. 3). It was found that indices calculated from SWIR decreased more significantly than others, especially for NDWI with CVs of 0.91 and 0.59 for poplar and locust trees, respectively. This was followed by a reversal of CI_{RE}, SRWI, and PRI, and a weak decrease in EVI and NDVI. Hence, it was clear that structurally oriented VIs (e.g., NDVI and EVI) were less sensitive than water- and chlorophyll-related indices to the foliage reflectance changes after tree removal. Thus, our results suggested that NDWI and CI_{RE} was the most suitable vegetation indices for detection of foliage reflectance changes after tree removal with the potential for timely detection of deforestation events in this region.

Relationships between meteorological parameters and the foliage spectral reflectance dynamics. Based on the correlation coefficients (R) between foliage spectral variables and meteorological parameters (Fig. 4), no spectral variables were found to be significantly correlated with wind speed and temperature. Conversely, relative humidity was found to be associated with decreasing reflectance in MODIS bands 1–7 for poplars and MODIS bands 1 and 3–7 for locust trees. PRI of the poplar trees also exhibited positive significant correlations ($p < 0.001$) with relative humidity. The heat stress index and dew point were associated with spectral variables of harvested tree foliage with a large value of R, particularly for reflectance in the MODIS SWIR bands (bands 6 and 7) and vegetation indices NDWI and SRWI. Furthermore, chlorophyll concentration exhibited a very significant correlation ($p < 0.001$) with spectral reflectance and with the indices of harvested tree foliage.

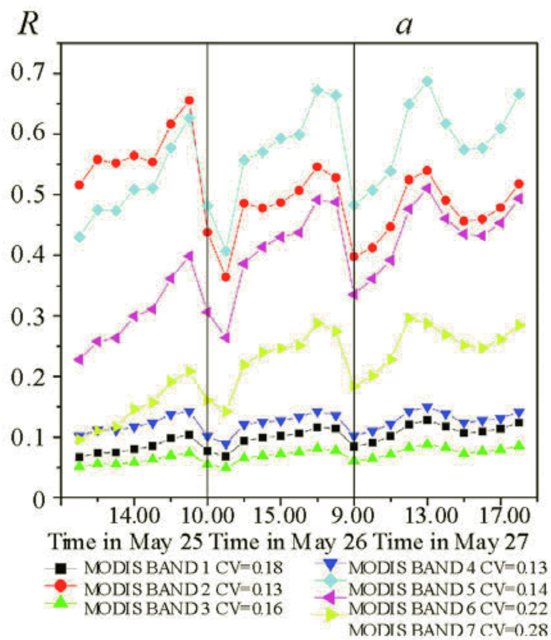

Fig. 1. Temporal variations in spectral reflectance of harvested tree foliage in MODIS bands 1–7 from May 25–27, 2011, for poplar (a) and locust trees (b).

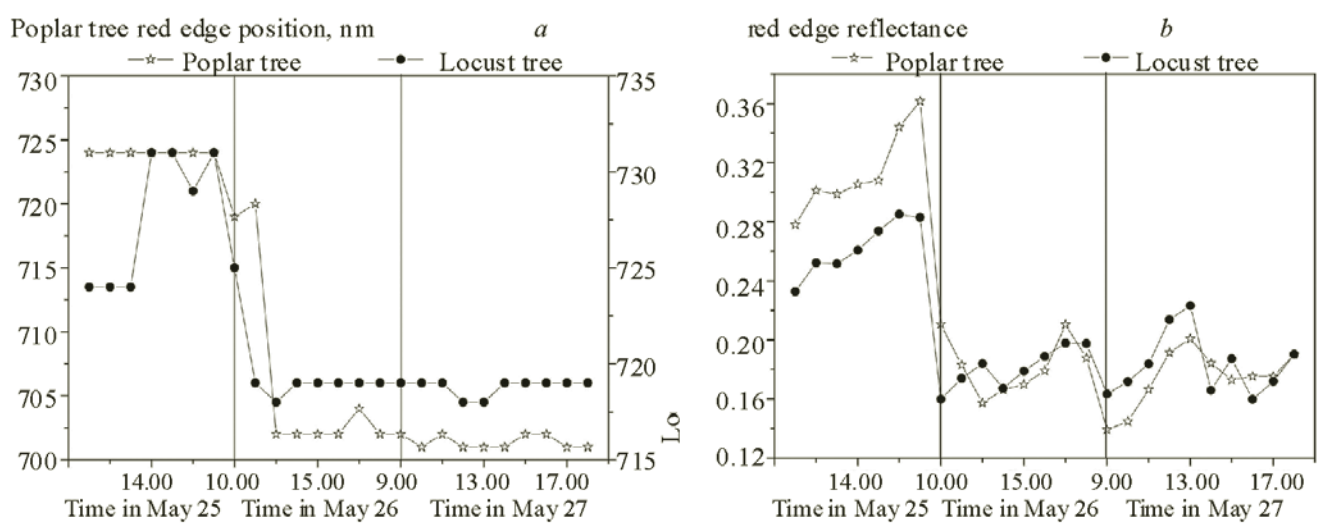

Fig. 2. Variations in the red-edge position (a) and red-edge reflectance (b) of harvested tree foliage with time after tree removal from May 25–27, 2011.

The heat stress index is a combination of temperature and humidity [29, 30], and the dew point is coupled with a number of atmospheric variables (e.g., mean surface temperature and relative humidity) [31]. Based on the relationships between meteorological parameters and spectral variables of the harvested tree foliage (Fig. 4), no significant correlations ($p < 0.01$) were found between individual meteorological parameters (e.g., wind speed, temperature, and relative humidity) and most of reflectance and indices. However, significant correlations ($p < 0.001$) were observed for synthesized meteorological parameters (e.g., heat stress index and dew-point temperature) with reflectance in the SWIR and chlorophyll-related indices (e.g., CI_{RE} and PRI).

Applicability and limitation. In the present study, we have found that spectral reflectance and vegetation indices was able to detect changes in tree foliage in the days immediately following harvest with related potential for monitoring of

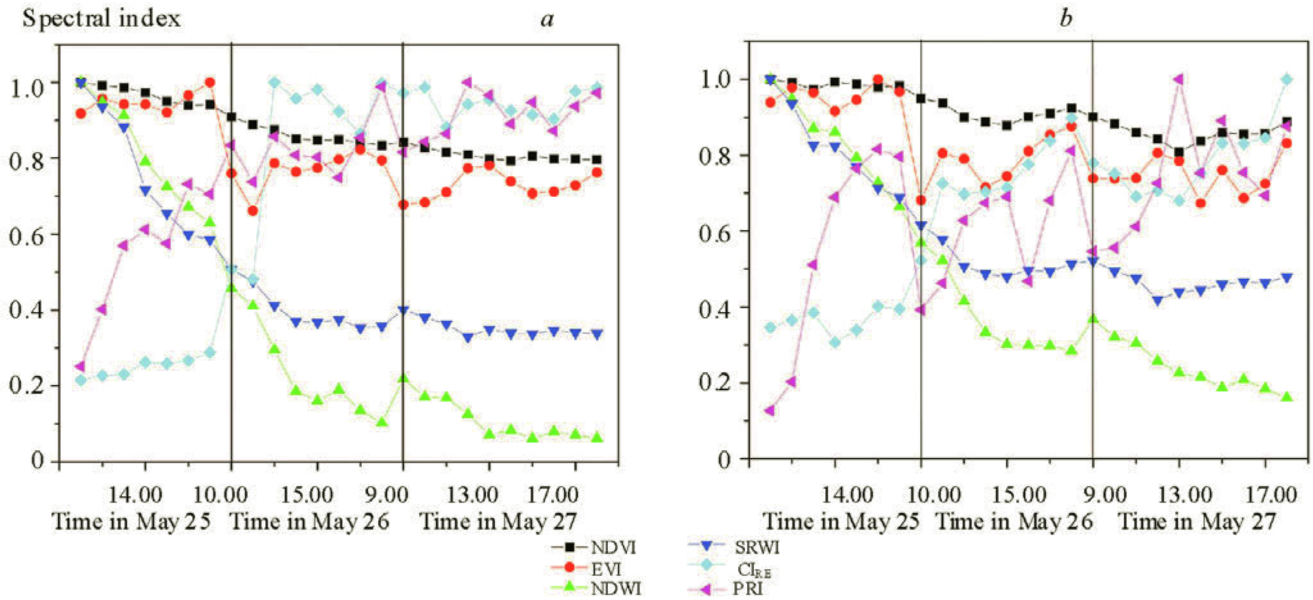

Fig. 3. Variations in vegetation indices of harvested tree foliage with time from May 25–27, 2011 after tree removal, for poplar (a) and locust trees (b).

deforestation. Owing to some limitations in our method, the following issues should be considered when determining the applicability of this method.

The process of deforestation is not the same as that of defoliation (or withering); the latter is typically gradual and characterized by loss of leaves due to insect infestation, disease, environmental change (e.g., drought), or normal seasonal change (e.g., from summer to fall) for deciduous trees [32–34]. Conversely, the process of deforestation is sudden. Based on temporal variations in the spectral reflectance and the indices of harvest tree foliage (Figs. 2 and 3), significant changes in the red-edge position and sharp decreases in reflectance were observed on the second day after harvest, followed by small fluctuations. The same patterns were observed for NDWI and CI_{RE}. We therefore propose comparing spectral variables of harvested tree foliage before and after a deforestation event as a method of detecting deforestation. In this method, red-edge position, reflectance in the SWIR bands, and water- and chlorophyll-related indices (e.g., NDWI and CI_{RE}) were the primary variables. In addition, we suggest consulting any long-term historical remote sensing records that may be available to capture seasonal patterns of proposed spectral variables following a deforestation event, and this will help to differentiate between deforestation and defoliation.

In this study, we convolved spectral reflectance data into MODIS wavebands using spectral response functions to assess the capability of broadband sensors for detecting changes in spectral properties of tree foliage after deforestation. However, we did not resolve the scaling problem of coupling remote sensing data with that from a field spectroradiometer. The spectral indices proposed to detect changes in harvested tree foliage after deforestation were NDWI and CI_{RE}, which can be calculated from multispectral and hyperspectral images obtained from airborne sensors and satellites. Thus, many sources of remote sensing data should be available for this method. MODIS data (e.g., reflectance product with a spatial resolution of about 500 m) have an advantage in monitoring a regional forest clearing but are not adequate for a small or sparse forest area, where the method of spectral unmixing or a combination with other higher resolution images helps to detect sub-pixel changes [35–37]. Therefore, additional experimental research combined with other methods will be required to detect deforestation directly from multi-source remote sensing data in future study.

Poplar and locust trees are deciduous plants that are widely distributed in temperate zones. The proposed spectral reflectance changes in short-wave infrared bands, red-edge position, and vegetation indices (NDWI and CI_{RE}) are related to canopy moisture and chlorophyll content [22]. Loss of water and chlorophyll is the primary reason for the time-sensitive nature of our proposed spectral indices for detecting the spectral changes in the tree foliage after deforestation. For evergreen forests, which should not lose water or chlorophyll as quickly as deciduous trees after deforestation, the starting day of foliage spectral changes is not expected to be as soon as two days following harvest. Furthermore, for deciduous species, the

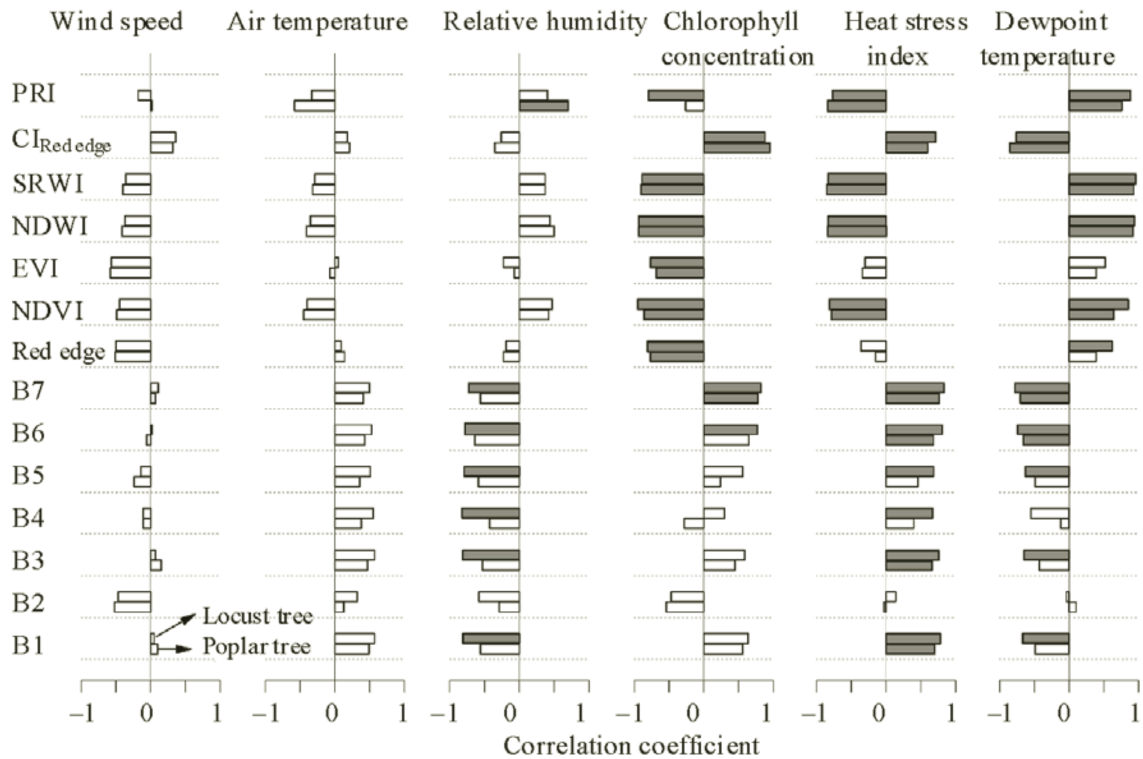

Fig. 4. Correlation coefficients (R) between spectral variables (reflectance and vegetation indices) of harvested tree foliage and meteorological parameters."B1-B7" and "Red edge" denote reflectance in MODIS bands 1–7 and the red-edge position, respectively. For each spectral variable, the bottom and upper bars denote poplar and locust trees, as shown by the arrows in the figure. The gray bars on the right and left sides of the y axis indicate the positive and negative significant correlations ($p < 0.001$), respectively.

proposed method can only be applied during the leaf-on period. Based on the relationships between spectral reflectance and vegetation indices of the harvested tree foliage and meteorological parameters (Fig. 4), the success of the proposed method, particularly with regard to the start time of tree foliage change detection, may be dependent on prevailing environmental conditions. This is particularly true in climates with significant seasonal variation. Our experiment was conducted on very clear and sunny days with a heat stress index of about 25^{o}C and a dew point of about 10^{o}C. In future studies, we will conduct more experiments incorporating different environment conditions and seasonal effects, and including the same measurements over about 3-day period before deforestation. Additional forest types and tree samples should also be considered to validate the applicability of our method.

The forest background must also be considered in determining the applicability of our method. In this study, we ignored the influences of the background that would typically occur under a forest canopy because no background appeared in the field of view in our experiments. Our proposed method was based on comparisons of spectral variables before and after a deforestation event, with particular attention given to sudden changes in these variables. Theoretically, we believe our proposed method can be used to detect tree foliage changes and has potential for monitoring deforestation in an area dominated by deciduous forest with bare or sparse vegetation background. However, the disturbance generated by the background should be considered in the area where the understory is comprised of heavy vegetation. Our proposed method is not applicable to forest harvesting processes in which trees are removed from the forest and immediately taken away for processing, leaving only slash/debris and understory vegetation behind. It is only applicable to deforestation methods that leave foliage of harvested trees in a place for several days following harvest.

Conclusions. For the present study, we chose poplar and locust trees for field experiments conducted over three consecutive sunny days. We used a spectroradiometer and a weather meter to explore the time sensitivities of spectral reflectance and vegetation indices of tree foliage after harvesting. It was found that reflectance in SWIR bands and the red-edge position and water- and chlorophyll-related indices (e.g., NDWI and $CI_{red\ edge}$) were more time-sensitive to harvested tree foliage changes. Accordingly, these are proposed as primary indicators for detection of foliage changes, with these having potential for deforestation monitoring. Significant correlations ($p < 0.001$) were observed between synthesized meteorological parameters (e.g., heat stress index and dew point) and spectral variables, and the second day after tree removal was found to be a suitable time to start detection, under a heat stress index of about 25°C or a dew point of about 10°C. To address the limitations of our study, future studies will focus primarily on monitoring deforestation over a large area with additional forest types using airborne sensors or satellite images. In particular, we intend to incorporate the influences of the understory and different environment conditions.

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