Remote Diagnosis of Tree Vigor in National Natural Heritage Using Digital Hyperspectral Image Analysis

Soo Young Nam [1], Su Hyun Kim [2], Jun Seok Lee [3], Yu Jeong Ha [4], Jae Yong Lee [5]

[1] Dept. of Heritage Science and Technology Studies, Graduate School of Korea Heritage, Korea National University of Heritage, South Korea – 20242099@knuh.ac.kr
[2] Dept. of Policy Research, Chungcheongnam-Do Institute of History and Culture, South Korea - ksh980314@naver.com
[3] Dept. of Heritage Science and Technology Studies, Graduate School of Korea Heritage, Korea National University of Heritage, South Korea – dlwnstjrz@gmail.com
[4] Dept. of Heritage Science and Technology Studies, Graduate School of Korea Heritage, Korea National University of Heritage, South Korea – yuj_0627@naver.com
[5] Dept. of Traditional Landscape Architecture, Korea National University of Heritage, South Korea - leejaeyong82@knuh.ac.kr

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Abstract

This study aims to non-destructively diagnose the growth condition of old-giant-trees designated as natural heritage by identifying vegetation indices and wavelength ranges using hyperspectral images. The main findings are as follows. First, the study established a method for acquiring hyperspectral images of trees in outdoor environments. It recommends a 20-meter standoff distance, which enables full coverage of the canopy region while ensuring stable acquisition of spectral data from the leaves. Second, vegetation indices suitable for diagnosing tree vigor were derived for zelkova, ginkgo, and pine, which are tree species that account for a high proportion of old-giant-trees designated as natural heritage. The results show that vegetation indices can effectively replace conventional light efficiency indicators. In the case of zelkova, the specific bands used to calculate indices with high correlation to light efficiency were identified. Third, a regression equation for the light efficiency indicator was developed and applied to canopy-level hyperspectral images, demonstrating that vegetation indices derived from selected wavelength ranges can be used to diagnose tree growth condition. This study is significant in that it proposes a method for quantitatively diagnosing the growth condition of old-giant-trees across their entire canopy using hyperspectral images. The findings can be applied as a scientific, non-destructive management technique for conserving the physiological characteristics and historical value of old-giant-trees designated as natural heritage.

1. Introduction

To preserve the value of old-giant-trees designated as national natural heritage, continuous monitoring of their growth condition is essential. However, these trees, while historically significant, are also physiologically aged and thus highly sensitive to changes in their growth condition. As a result, diagnostic methods involving direct physical contact may damage tissue and potentially disrupt physiological functions over time. Moreover, most old-giant-trees have considerable height and complex structures, making structural access difficult. This underscores the need to develop a technique for managing tree vigor through a non-contact approach.
Although attempts have been made to diagnose tree growth condition using hyperspectral images, acquiring such images in outdoor environments typically requires a short imaging distance, which limits their applicability for diagnosing the vigor of old-giant-trees. PARK(2023) diagnosed the health of zelkova using a ground-based spectroradiometer (PSR-1100F) to extract point-based hyperspectral data and analyzed its correlation with light efficiency indicators, ultimately identifying suitable vegetation indices and wavelength ranges. By capturing images at a distance of 2-3 cm from the sensor using harvested zelkova leaves, the study obtained pure data minimally affected by atmospheric noise, which is an important contribution. However, because the imaging was performed on individual leaves at close range, the method is difficult to apply to large trees such as old-giant-trees.

If hyperspectral images can be used to diagnose tree vigor, it would enable more quantitative diagnostics and scientific management without harming natural heritage. Therefore, this study aims to diagnose the growth condition of old-giant-trees designated as natural heritage through non-destructive means by identifying appropriate vegetation indices and wavelength ranges based on hyperspectral images.

2. Materials and Methods

This study followed a sequential process of collecting leaves and measuring light efficiency indicators, hyperspectral imaging of both leaves and canopies, preprocessing the images, analyzing correlations between vegetation indices and light efficiency indicators, selecting appropriate wavelength ranges, and diagnosing tree growth condition through regression analysis. The study focused on three tree species: zelkova (*Zelkova serrata*(Thunb.) Makino), ginkgo (*Ginkgo biloba* L.), and pine (*Pinus densiflora* Siebold & Zucc.), which are frequently designated as old-giant-trees within natural heritage and are key targets for conservation management. To ensure operability of the equipment and efficiency of the research process, the study was conducted at the Korea National University of Heritage, located in Buyeo-gun, Chungcheongnam-do, South Korea. This location provided continuous access for the research team and convenient conditions for storing and installing equipment. Based on these

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considerations, three vigorous young trees from each species were selected (Figure 1).

a. Zelkova b. Ginko c. Pine

Figure 1. Target canopies for imaging

2.1 Measurement of Light Efficiency Indicators

Tree light efficiency was measured using five indicators: Fv/Fm, Y(II), NPQ, Y(NO), and Y(NPQ). Fv/Fm (Maximum Quantum Yield) represents the maximum quantum yield of photochemical reactions and serves as a indicator of photosynthetic capacity. In dark-adapted leaves, this value reflects the tree’s maximum potential for photosynthesis. Y(II) (Effective Quantum Yield) measures the effective quantum yield under ambient light and, like Fv/Fm, reflects photosynthetic capacity. NPQ (Non-Photochemical Fluorescence Quenching) indicates the amount of energy dissipated as heat via photoprotective mechanisms, which is an essential process for shielding plants from light-induced damage. Y(NO) represents the proportion of energy dissipated as heat and fluorescence through non-photochemical pathways. Higher values indicate a reduced capacity for photoprotection against light-induced damage. Y(NPQ) represents the proportion of NPQ and corresponds to the proportion of energy dissipated as heat. Higher values suggest stronger photoprotective capacity. Together, the ratios of Y(II), Y(NPQ), and Y(NO) help identify energy dissipated as heat and provide information about tree health. The sum of Y(II), Y(NPQ), and Y(NO) should equal 1. When Y(NO) exceeds Y(NPQ), it may indicate compromised tree health.

Leaves were collected from the east, west, and south-facing sides of each tree, excluding the north-facing side due to insufficient sunlight. For zelkova and ginkgo, 80 leaves per species were collected, with 40 from the front surface and 40 from the back surface. Pine leaves, which do not have distinguishable surfaces, were collected in a set of 40. Light efficiency indicators were measured using the MINI-PAM-II model by WALZ. A dark adaptation clip was attached to the measurement site to block ambient light, and the samples were dark-adapted for 20 minutes before measuring Fv/Fm. The Ft value, used as a reference for measuring Fv/Fm, was set by adjusting the sensor’s light intensity to a range of 250-500 using the Measuring Light Intense setting. Through the Induction Curve experiment, the effective quantum yield Y(II), the proportion of energy dissipated as heat Y(NPQ), the amount of energy emitted as fluorescence Y(NO), and the amount of energy dissipated as heat NPQ were measured (Figure 2).

a. Dark adaptation of leaves b. Induction Curve

Figure 2. Process of measuring light efficiency indicators

2.2 Hyperspectral Imaging

Since hyperspectral imaging is highly sensitive to light intensity, imaging was conducted during periods when solar elevation was high and light intensity was sufficient, specifically, when photosynthetic activity was expected to be optimal. Leaf and canopy imaging was carried out from the east and south-facing sides between 9:00 AM and 3:00 PM, when light intensity ranged from 800 to 1,200 mol/m^2/s. The standoff distance was set to 20 meters to ensure full coverage of each tree, allowing for application of the method in diagnosing the growth condition of the entire canopy. The camera height was fixed at 1.7-1.8 meters to accommodate the length of the connection cable. A white reflectance panel was installed so that it would be included in the image. The hyperspectral camera used was the Fx10e model by Specim. Under these conditions, the camera was configured with an exposure time of 6.3-7 milliseconds and a frame rate of 28-33 Hz. For leaf imaging, a 120×150 cm measurement panel was constructed by mounting a black, non-reflective cloth onto a metal frame, and leaves were fixed onto the panel for imaging (Figure 3).

Figure 3. Leaves fixed onto the measurement panel

2.3 Preprocessing

To correct the spectral reflectance of hyperspectral images to 100%, normalization was performed using HyScope by Geostory. The reflectance of the white reference panel within the images was set to 99%. After normalization, spectral smoothing was applied using the Savitzky-Golay method in ENVI. To separate the leaves from the background in the canopy images, anomaly detection was employed. The Degree of Smoothing Polynomial was set to 7, 0, and 2, which were values chosen for their ability to preserve the original spectral characteristics while correcting spectral reflectance values exceeding 100. Anomaly detection was also applied to separate the leaves from the background in the hyperspectral images of leaves. For canopy hyperspectral images, the CIVE method was used to distinguish the canopy from surrounding complex backgrounds.

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2.4 Correlation Analysis

A correlation analysis was performed between the vegetation indices and light efficiency indicators. The vegetation indices analyzed included NDVI, GNDVI, GCI, MCARI, RENDVI, MRENDVI, CRI1·2, and ARI1·2, while the light efficiency indicators included Y(II), Y(NO), Y(NPQ), Fv/Fm, and NPQ. To calculate correlation coefficients, the spectral bands used to derive vegetation indices in previous studies were modified by ±30 nm. Bands were selected if the correlation coefficient between a vegetation index and a light efficiency indicator was 0.35 or higher and the p-value indicated statistical significance at 5% or less ($P \leq 0.05$).

2.5 Regression Analysis

The correlation between vegetation indices, calculated using the selected wavelength ranges, and light efficiency indicators was examined, along with an evaluation of similarity between the indicators. Stepwise linear regression was conducted by setting light efficiency indicators as dependent variables and vegetation indices as independent variables for each tree species. Variables showing multicollinearity were excluded from the model. The fit of the regression models was validated using the Durbin-Watson test and t-tests. The resulting regression equations between light efficiency indicators and vegetation indices were then applied to canopy hyperspectral images to diagnose tree growth condition.

3. Result and Discussion

3.1 Selection of Wavelength Ranges Suitable for Diagnosing Tree Vigor

Vegetation indices are calculated from specific combinations of band values, and hyperspectral images are composed of bands segmented at the nanometer scale. The results of vegetation indices can vary substantially depending on the band values used in their calculation. Therefore, to derive vegetation indices suitable for diagnosing tree vigor from leaf images taken at a distance of 20 meters, it is essential to carefully select appropriate bands. In this study, the bands used to calculate vegetation indices that showed strong correlations with light efficiency indicators were selected.

3.1.1 Zelkova showed correlation coefficients of 0.4 or higher between Y(II) and several vegetation indices including NDVI, GNDVI, GCI, and RENDVI. Accordingly, bands used in vegetation indices that exhibited correlation coefficients of 0.4 or greater with Y(II) were selected. The wavelength ranges suitable for diagnosing tree vigor in zelkova were as follows: in the NIR region, 781 nm and 763 nm for NDVI, GNDVI, and GCI; in the RED region, 731 nm, 718 nm, 690 nm, and 687 nm for RENDVI and MRENDVI, and 695 nm, 692 nm, and 660 nm for CRI2 and MCARI; in the Green region, 501 nm for CRI1 and CRI2, 539 nm for CRI1, 550 nm for GNDVI and GCI, 540 nm and 523 nm for PRI, and 543 nm for MCARI; in the Blue region, 407 nm for MRENDVI.
Ginkgo showed the highest number of vegetation indices with correlation coefficients of 0.3 or higher with Y(NO), including NDVI, GNDVI, RENDVI, PRI, CRI1 and CRI2. Based on this, bands used in vegetation indices that showed correlation coefficients of 0.3 or greater with Y(NO) were selected. The wavelength ranges suitable for diagnosing tree vigor in ginkgo were as follows: in the NIR region, 792 nm and 776 nm for NDVI, GNDVI, and GCI; in the RED region, 746 nm and 669 nm for RENDVI and MRENDVI, and 692 nm, 676 nm, and 660 nm for CRI2 and MCARI; in the Green region, 470 nm for CRI1 and CRI2, 548 nm for CRI1, 543 nm and 531 nm for MCARI and GCI, and 551 nm and 531 nm for PRI; in the Blue region, 412 nm for MRENDVI.
Pine showed correlation coefficients of 0.35 or higher between Y(NPQ) and vegetation indices including PRI, MCARI, RENDVI, and MRENDVI. Based on this, bands used in vegetation indices with correlation coefficients of 0.35 or greater with Y(NPQ) were selected. The wavelength ranges suitable for diagnosing tree vigor in pine were as follows: in the NIR region, 776 nm, 768 nm, and 763 nm for NDVI, GNDVI, and GCI; in the RED region, 747 nm and 691 nm for RENDVI and MRENDVI, and 660 nm and 645 nm for MCARI; in the Green region, 514 nm and 497 nm for CRI1, 550 nm and 543 nm for MCARI and GCI, and 551 nm and 531 nm for PRI; in the Blue region, 432 nm for MRENDVI.

3.1.2 Comparison of wavelength ranges selected by tree species: Wavelength ranges selected as suitable for diagnosing tree vigor were compared across species to identify associations with specific bands or vegetation indices (Figure 4). For zelkova, ginkgo, and pine, GNDVI and GCI produced the highest correlation coefficients when the same wavelengths were used across species, indicating that the two indices likely exhibit similar spectral behavior. For PRI, ginkgo and pine shared the wavelengths 551 nm and 531 nm, while zelkova used 540 nm and 523 nm. For MCARI, ginkgo and zelkova shared 692 nm, 660 nm, and 543 nm, while pine used 660 nm, 645 nm, and 550 nm. GNDVI in ginkgo and PRI in both ginkgo and pine shared 531 nm. All three species shared 660 nm in the red region for MCARI. In ginkgo, RENDVI and MRENDVI shared red-region wavelengths of 746 nm and 699 nm. The red region in MCARI, RENDVI, and MRENDVI, which are narrow-band vegetation indices sensitive to tree stress, spanned a broad range from 660 nm to 746 nm. In contrast, the correlation coefficients for the selected wavelengths were 0.35 or below for NDVI, GNDVI, CRI1, CRI2, and GCI in pine, and for PRI in zelkova.

3.2 Diagnosis of Tree Growth condition Using Correlation and Regression Analysis

3.2.1 Correlation between vegetation indices derived from selected wavelengths and light efficiency: In zelkova, the vegetation indices NDVI, GNDVI, PRI, GCI, MCARI, RENDVI, MRENDVI, and CRI1 and CRI2 each exhibited significant correlations with Y(II), with coefficients of 0.4 or higher at the 0.01 significance level. Notably, Y(II) showed strong positive correlations with NDVI, GNDVI, GCI, and RENDVI. Because Y(II) increases when photosynthetic efficiency under ambient light is high, and these indices also rise when the tree has sufficient chlorophyll and water content, this correlation reflects a healthy growth state. Conversely, Y(II) demonstrated a strong negative correlation with MCARI. Since high MCARI values indicate reduced chlorophyll content, this negative correlation with Y(II) is expected (Table 1).

	NDVI	GNDVI	PRI	GCI	MCARI	RENDVI	MRENDVI	CRI1	CRI2
Y(NPQ)	-0.282*	-0.318**	0.194	-0.326**	0.273*	-0.279*	-0.275	-0.219	-0.253*
NPQ	-0.073	-0.132	0.042	-0.145	0.163	-0.051	-0.124	-0.033	-0.089
Fv/Fm	0.173	0.128	-0.104	0.098	-0.159	0.159	0.182	0.108	0.071
Y(II)	0.451**	0.450**	-0.336**	0.457**	-0.367**	0.463**	0.395**	0.362**	0.388**
Y(NO)	-0.147	-0.090	0.135	-0.087	0.054	-0.168	-0.086	-0.154	-0.111

* $p<0.05$, ** $p<0.01$

Table 1. Correlation Analysis Between Vegetation Indices and Light Efficiency in Zelkova

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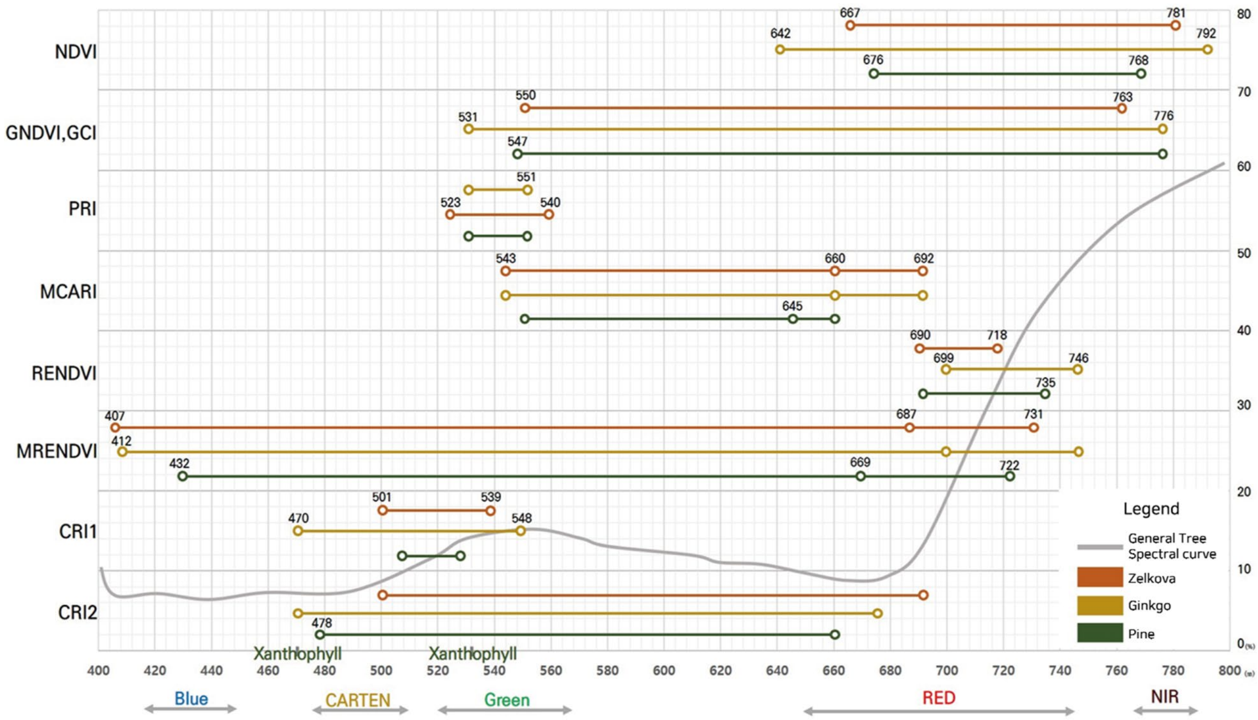

Figure 4. VI Wavelength Bands Selected for Each Species

In ginkgo, the vegetation indices NDVI, GNDVI, PRI, GCI, MCARI, RENDVI, MRENDVI, and CRI1 and CRI2 exhibited correlation coefficients of 0.38 or higher with Y(NO) at the 0.01 significance level. Notably, Y(NO) showed strong negative correlations with NDVI, GNDVI, GCI, and CRI1 and CRI2, while MCARI and PRI demonstrated strong positive correlations. As Y(NO) increased, NDVI, GNDVI, GCI, and RENDVI tended to decrease. Because Y(NO) represents the amount of energy emitted as fluorescence, its value becomes larger when the tree is in poor health. In contrast, NDVI, GNDVI, GCI, and RENDVI are indices that reflect chlorophyll and water content in trees and increase under healthy conditions, resulting in a negative relationship with Y(NO). Since higher MCARI values indicate lower chlorophyll content, a positive correlation with Y(NO) is expected (Table 2).

	NDVI	GNDVI	PRI	GCI	MCARI	RENDVI	MRENDVI	CRI1	CRI2
Y(NPQ)	0.292*	0.208	-0.105	0.137	-0.221	0.318*	0.242*	0.194	-0.270
NPQ	0.259*	0.272*	-0.237	0.243*	-0.261	0.250*	0.195	0.245	0.222
Fv/Fm	0.296**	0.282*	-0.282	0.256	-0.322	0.325**	0.318 **	0.303	0.216
Y(II)	0.027	0.130	-0.205*	0.187	-0.135	-0.020	0.049	0.135	0.336**
Y(NO)	-0.417**	-0.453**	0.426**	-0.442 **	0.478**	-0.384**	-0.383**	-0.443**	-0.442**

* p<0.05, ** p<0.01

Table 2. Correlation Analysis Between Vegetation Indices and Light Efficiency in Ginkgo

In pine, the vegetation indices PRI, MCARI, RENDVI, and MRENDVI exhibited significant correlations of 0.35 or higher with Y(NPQ) at the 0.01 significance level. Notably, Y(NPQ) showed strong negative correlations with MRENDVI, RENDVI, and MCARI, while PRI demonstrated a positive correlation. As Y(NPQ) increased, the values of RENDVI, MRENDVI, MCARI, and NDVI tended to decrease. Y(NPQ) represents energy dissipation through non-photochemical quenching, and although its value may be relatively high when the tree is healthier compared to Y(NO), it generally increases during poor health as excess light energy is released as heat. Because NDVI, RENDVI, and MRENDVI increase with higher chlorophyll and water content under healthy conditions, they exhibit negative correlations with Y(NPQ) (Table 3).

	NDVI	GNDVI	PRI	GCI	MCARI	RENDVI	MRENDVI	CRI1	CRI2
Y(NPQ)	-0.266	0.097	0.357*	0.062	-0.369*	-0.406*	-0.416**	0.026	0.046
NPQ	-0.231	0.132	0.242	0.100	-0.310	-0.341*	-0.361**	0.161	0.201
Fv/Fm	0.107	0.070	-0.024	0.073	-0.117	-0.004	-0.049	0.297	0.135
Y(II)	0.075	0.047	-0.169	0.053	0.036	0.118	0.105	0.223	0.200
Y(NO)	0.165	-0.136	-0.152	-0.110	0.298	0.248	0.270	-0.250	-0.245

* p<0.05, ** p<0.01

Table 3. Correlation Analysis Between Vegetation Indices and Light Efficiency in Pine

3.2.2 Derivation of regression equations between light efficiency indicators and vegetation indices: For zelkova, the Variance Inflation Factor (VIF), an indicator used to assess multicollinearity, was 1, indicating that multicollinearity was not an issue. Accordingly, GCI was interpreted as having an impact on light efficiency. GCI explained 29.6% of the variance in Y(II), and the regression model ($F = 29.037$) was statistically significant at the $p < 0.01$ level. The Durbin-Watson statistic was 1.609, which is close to 2, indicating low residual autocorrelation and showing that the regression model was appropriate. The t-test result indicated that the slope relative to the intercept was 0.001 or lower, confirming the statistical significance of the regression model (Table 4). The regression equation derived from the analysis between Y(II) and GCI is as follows (Eq 1).

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dependent variable	Independent Variable	*B*	β	t	*R*	*R²*	*F*
Y(II)	constant	0.156		8.699**			
	GCI	0.024	0.544	5.389**	0.544	0.296	29.037**

* p<0.05, ** p<0.01

Table 4. Regression Analysis for Zelkova

$$Y(II) = 0.024 \times GCI + 0.156, \quad (1)$$

For ginkgo, the VIF was 1, indicating that multicollinearity was not an issue. Accordingly, MCARI was interpreted as having an impact on light efficiency. MCARI explained 30.5% of the variance in Y(NO), and the regression model (F = 27.622) was statistically significant at the p < 0.001 level. The Durbin-Watson statistic was 1.871, which is close to 2, indicating low residual autocorrelation and showing that the regression model was appropriate. The t-test result indicated that the slope relative to the intercept was 0.001 or lower, confirming the statistical significance of the regression model (Table 5). The regression equation derived from the analysis between Y(NO) and MCARI is as follows (Eq 2).

dependent variable	Independent Variable	*B*	β	t	*R*	*R²*	*F*
Y(NO)	constant	0.144		9.595**			
	MCARI	0.015	0.552	5.256**	0.552	0.305	27.622**

* p<0.05, ** p<0.01

Table 5. Regression Analysis for Ginkgo

$$Y(NO) = 0.015 \times MCARI + 0.144, \quad (2)$$

For pine, the VIF was 1, indicating that multicollinearity was not an issue. Accordingly, MRENDVI was interpreted as having an impact on light efficiency. MRENDVI explained 22.8% of the variance in Y(NPQ), and the regression model (F = 9.430) was statistically significant at the p < 0.04 level. The Durbin-Watson statistic was 2.017, which is very close to 2, indicating low residual autocorrelation and showing that the regression model was appropriate. The t-test result indicated that the slope relative to the intercept was 0.004 or lower, confirming the statistical significance of the regression model (Table 6). The regression equation derived from the analysis between Y(NPQ) and MRENDVI is as follows (Eq 3).

dependent variable	Independent Variable	*B*	β	t	*R*	*R²*	*F*
Y(NPQ)	constant	0.775		7.498**			
	MRENDVI	-0.401	-0.477	-3.071*	0.477	0.228	9.430**

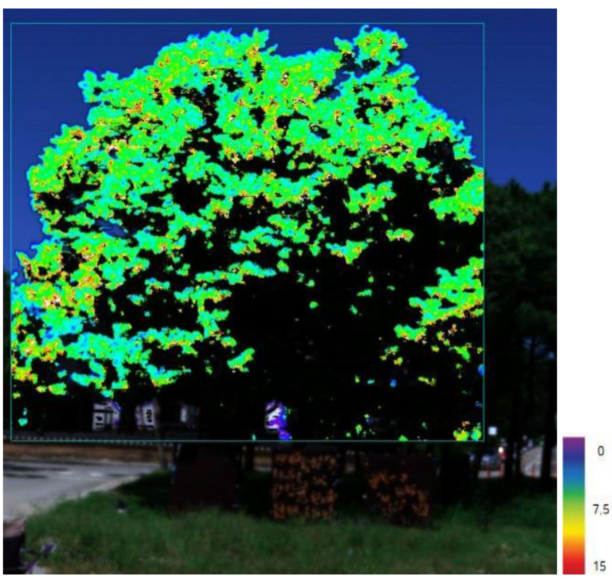
* p<0.05, ** p<0.01

Table 6. Regression Analysis for Pine

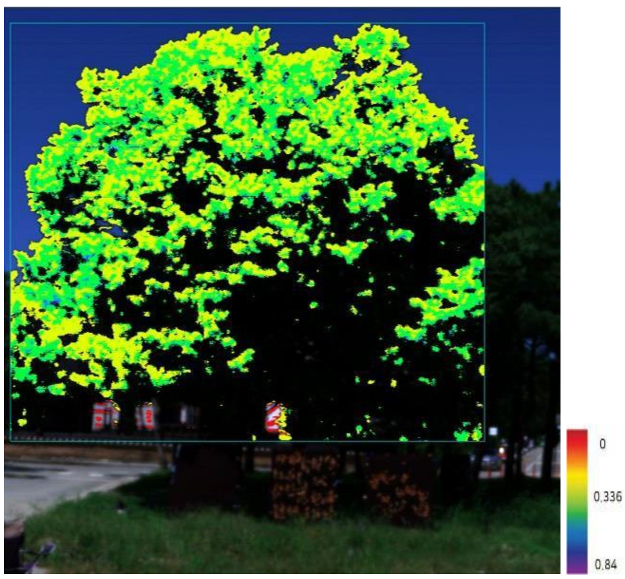
$$Y(NPQ) = -0.401 \times MRENDVI + 0.775, \quad (3)$$

3.2.3 Diagnosis of tree growth condition using vegetation index analysis: Vegetation indices calculated from the bands selected through correlation analysis were applied to the hyperspectral images of the trees to validate the results. Subsequently, light efficiency values were estimated using the derived regression equations, enabling health diagnoses for each individual large tree.

To assess the growth condition of zelkova, GCI was selected as the vegetation index most suitable for health diagnosis based on vegetation index comparison, correlation analysis, and regression analysis. The vegetation index calculated from the selected bands was applied to the hyperspectral image of zelkova, and the results were examined (Figure 5). The vegetation index ranged from 0 to 15, with higher GCI values reflecting better health. In zelkova, values between 0.6 and 10 were most commonly observed. Based on the regression equation, Y(II) values below 0.133 were classified as indicating poor health, while values of 0.133 or higher were considered healthy. The Y(II) analysis showed that most values exceeded 0.168, suggesting that the majority of leaves comprising the canopy were in good condition.



a. GCI

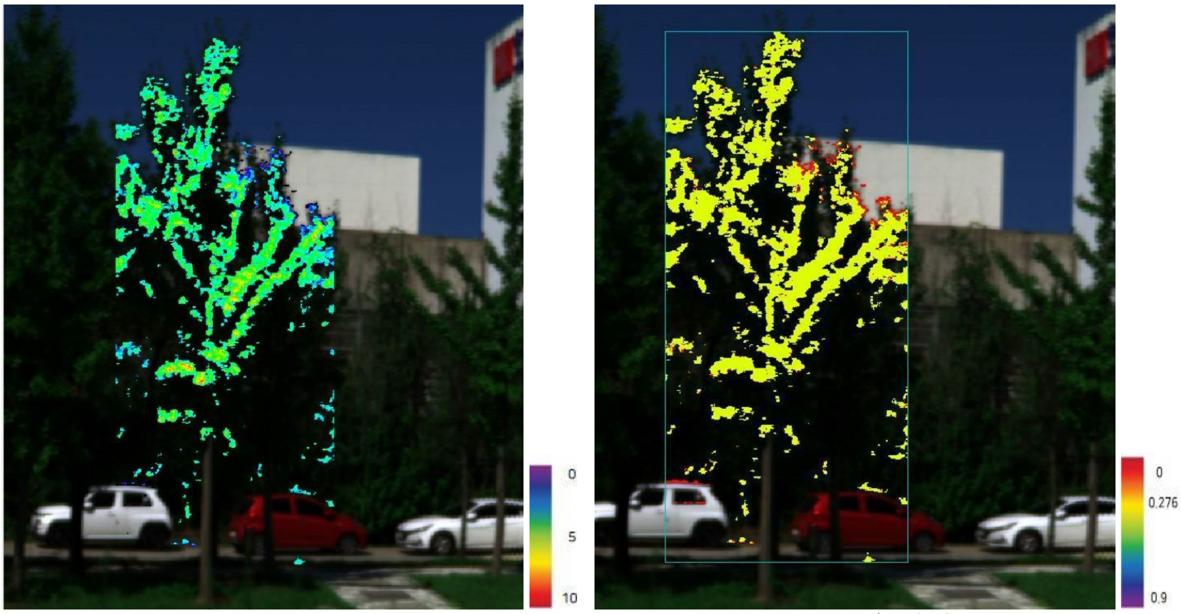


b. Y(Ⅱ)

Figure 5. Results of Zelkova Vigor Diagnosis

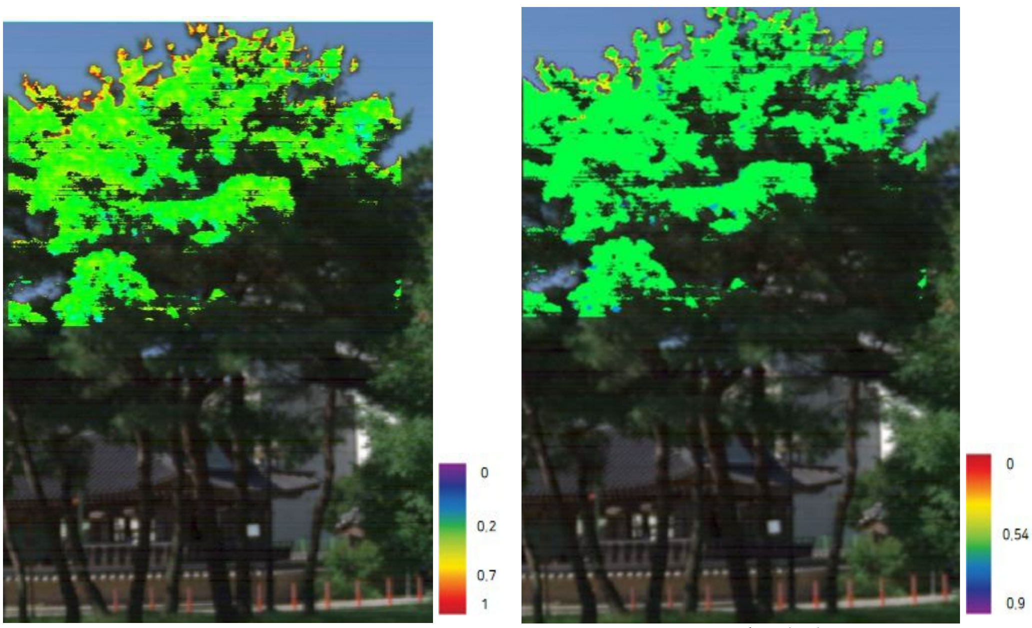
To assess the growth condition of ginkgo, MCARI was selected as the vegetation index most effective for health diagnosis based on vegetation index comparison, correlation analysis, and regression analysis. The vegetation index calculated from the selected bands was applied to the hyperspectral image of ginkgo, and the results were examined (Figure 6). The vegetation index ranged from 0 to 10, with higher MCARI values reflecting poorer health. In ginkgo, values between 0 and 5 were most frequently observed. Based on the regression equation, Y(NO) values above 0.276 were classified as indicating poor health. The Y(NO) analysis showed that most of the ginkgo were in a healthy condition up to approximately 0.30. As Y(NO) values increase toward the green range, areas appearing green rather than yellow in the image were interpreted as being in poorer condition.

To assess the growth condition of pine, MRENDVI was selected as the vegetation index most effective for health diagnosis based on vegetation index comparison, correlation analysis, and regression analysis. The vegetation index calculated from the selected bands was applied to the hyperspectral image of pine, and the results were examined (Figure 7). The vegetation index ranged from 0 to 1, with values between 0.2 and 0.7 indicating healthy conditions. In pine, values between 0.43 and 0.68 were the most frequent. Based on the regression equation, Y(NPQ) values outside the range of 0.458 to 0.628 were considered indicative of poor health. The Y(NPQ) analysis showed that most values fell between 0.4 and 0.6, confirming that the tree was generally in good health.



a. MCARI b. Y(NO)

Figure 6. Results of Ginkgo Vigor Diagnosis



a. MRENDVI b. Y(NO)

Figure 7. Results of Pine Vigor Diagnosis

4. Conclusions

The results of this study are summarized as follows.
First, a method for acquiring hyperspectral images of trees in outdoor environments was established. Imaging conditions were defined for a 20-meter standoff distance, which enables full coverage of the canopy region of old-giant-trees while maintaining stable acquisition of spectral data from the leaves. The hyperspectral camera used was the Fx10e model by Specim. Under light intensity conditions between 800 and 1,200 mol/㎡/s, the camera settings were configured with an exposure time of 6.3 to 7 milliseconds and a frame rate of 28 to 33 Hz.
Second, vegetation indices suitable for diagnosing tree vigor were identified for zelkova, ginkgo, and pine, which are species frequently designated as natural heritage old-giant-trees. The results confirmed that vegetation indices can serve as alternatives to light efficiency indicators. GCI was found to impact Y(II) in zelkova, MCARI to impact Y(NO) in ginkgo, and MRENDVI to impact Y(NPQ) in pine. In cases where strong correlations were observed between vegetation indices and light efficiency indicators, the associated bands used in calculating the indices were presented.
Third, regression equations for light efficiency indicators were derived, demonstrating that tree growth conditions can be diagnosed using vegetation indices calculated from the selected wavelength ranges. Specifically, regression equations were developed for Y(II) and GCI in zelkova, Y(NO) and MCARI in ginkgo, and Y(NPQ) and MRENDVI in pine. These equations were applied to the trees’ hyperspectral images to diagnose their growth conditions.
The results of this study offer a non-destructive, scientific management technique for conserving the physiological traits and historical value of old-giant-trees designated as natural heritage. However, the analysis was limited to a subset of designated species, and the correlation between light efficiency measured at the leaf level and image data may be reduced due to long-range imaging. To improve field applicability across all designated old-giant-tree species, future research should expand the analysis to additional species and develop methods for more accurately acquiring spectral data from leaves.

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