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Spectral reflectance properties of healthy and stressed coniferous trees

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This study investigates the properties of hyperspectral reflectance of healthy and stressed coniferous trees. Two coniferous tree species which naturally grow in Lithuania, Scots pine (*Pinus sylvestris* L.) and Norway spruce (*Picea abies* (L.) Karst.), as well as an introduced species, Siberian pine (*Pinus sibirica* Du Tour), were selected for the study. Hyperspectral reflectance data were collected under laboratory conditions by scanning the needles of healthy (no foliar loss) and stressed Norway spruce (foliar loss 66-70%), Scots pine (foliar loss 71-75%) and Siberian pine (foliar loss 86-90%) trees using a Themis Vision Systems VNIR 400H hyperspectral imaging camera. The spectrometer of the camera covers the spectral range of 400-1000 nm with the sampling interval of 0.6 nm. Simultaneously, the chlorophyll a and b content in the needles was determined by spectrophotometrically measuring the needles' absorbance of ethanol extracts. The statistical analyses included principal component analysis, analysis of variance and partial least squares regression techniques. Relatively large spectral differences between healthy and stressed trees were detected for Norway spruce needles: 884 out of 955 wavebands indicated a statistically different reflectance ($p < 0.05$). The reflectance associated with the stress level was statistically different ($p < 0.05$) in 767 and 698 out of 955 wavebands for Scots pine and Siberian pine, respectively. The most informative wavelengths for spectral separation between the needles taken from healthy and stressed trees were found in the following spectral ranges: 701.0-715.7 nm for Norway spruce, 706.1-718.2 nm for Scots pine, and 862.3-893.1 nm for Siberian pine. The relationship between the spectral reflectance properties of the needles and their chlorophyll content was also determined for each species. Waveband ranges (as well as single bands) most sensitive to changes in chlorophyll content were: 709.9-722.1 nm (715.6 nm) for Norway spruce; 709.3-721.4 nm (715.0 nm) for Scots pine; 710.6-722.7 nm (720.1 nm) for Siberian pine. In general, the study revealed that narrow-band based hyperspectral imaging has the potential for accurately detecting stress in coniferous trees.

Keywords: Conifers, Imaging Spectrometry, Hyperspectral Reflectance, Tree Stress, Waveband Selection

Introduction

Systematic forest health monitoring has been conducted in Europe for almost three decades. In 1985, the International Co-operative Programme on Assessment and Monitoring of Air Pollution Effects on Forests (ICP Forests) was launched under the Convention on Long-range Transboundary Air Pollution of the United Nations Economic Commission for Europe (UNECE) and standardized methods for forest monitoring were defined (Fischer & Lorenz 2011). Also, in 1998, Lithuania started a regular forest monitoring program using ICP methods and standards. Forest monitoring is performed using a network of observation plots scattered across the country. Crown defoliation is

one of the principal indicators of tree health (Ozolinčius & Stakenas 1996). Tree defoliation is visually assessed by comparing the foliage loss of an individual with a healthy reference tree of the same crown type in the vicinity using 5% units. The reference tree is based on a photograph of a local tree, representing a tree with full foliage, or a conceptual (imaginary) tree (Eichhorn et al. 2010). Defoliation assessment, therefore, relies on the experience and skills of the observer and tends to have some level of subjectivity.

Instrumental measurements of tree crown defoliation would substantially reduce the intrinsic subjectivity of defoliation assessments (Augustaitis et al. 2009, Bikuvienė & Mozgeris 2010, Mozgeris et al. 2011). Nu-

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merous studies have investigated the potential application of ground-based, airborne or spaceborne remote sensing techniques to assess tree defoliation. One example of ground-based instrumental measuring of defoliation includes the use of semi-automatic image analysis systems to assess crown transparency from photographs based on fractal analysis (Nobuya & Dobbertin 2004). Satellite and airborne remote sensing can also provide an alternative to traditional ground-based assessments of forest health (Ciesla 2000, Solberg et al. 2004, Wulder et al. 2006). However, assessing defoliation in this way may be difficult because of the associated costs of image acquisition, methodological issues in data processing, limited spatial, radiometric and temporal resolutions. Despite the numerous studies discussing the role of remote sensing in forest health assessment, very few examples of truly operational techniques are demonstrated. However, multispectral imaging, or more specifically, hyperspectral remote sensing, appears to have a strong potential for forest health assessment (Entcheva-Campbell et al. 2004, Somers et al. 2010, Cho et al. 2012).

Research in the field of hyperspectral imaging for forestry applications has increased significantly during the last decade. Hyperspectral imaging is expected to prove very useful in the remote identification of forest tree species as well as in the evaluation of forest health. Furthermore, with the advent of a new generation of hyperspectral cameras, such as the VNIR400H used in this study, the potential use of hyperspectral imaging for forest health monitoring should be investigated.

Hyperspectral remote sensing, also called “hyperspectral imaging” or “imaging spec-

trometry”, is based on a combination of imaging and spectroscopy in a single scheme. Hyperspectral sensors are instruments that acquire images of an object in very many and very narrow (nanometre level) contiguous spectral bands. Depending on the construction, they can sense the electromagnetic waves in the ultraviolet, visible, near infrared, mid infrared and even thermal ranges of the electromagnetic spectrum. These instruments can collect from hundreds to more than a thousand bands of data for every pixel of an image. Hyperspectral sensing has the potential for precise identification, discrimination, and classification of various objects and their features. For example, an object in a hyperspectral image can be classified according to its physiological, chemical and other type of physical characteristic. Hyperspectral remote sensing involves hundreds of wavebands and very narrow spectral intervals, typically leading to large volumes of data. Furthermore, neighbouring wavebands have a high degree of correlation, resulting in informational redundancy (Thenkabail et al. 2004) created by oversampling. Spectral signals are sampled at very small steps to allow for the discrimination of very narrow spectral features (Shaw & Manolakis 2002). Researchers dealing with hyperspectral data face new challenges such as the treatment of high-dimensional data and a requirement for extensive computation capacity and data storage (Varshney & Arora 2004).

Research related to the spectral reflectance properties of trees (at the leaf, crown or entire stand level) has been conducted for several decades. Numerous studies have shown that reflected electromagnetic radiation recorded in narrow spectral bands can provide informative data about the condition of plants and how plants change over time, and also enable a researcher to remotely analyze the plants’ physiological characteristics and chemical properties (Entcheva-Campbell et al. 2004, Huber et al. 2008, Moorthy et al. 2008, Cho et al. 2012, Wang & Li 2012). Studies on the application of hyperspectral imaging can be divided roughly into two categories: (1) employment of airborne or spaceborne hyperspectral sensors - in this case the hyperspectral images are acquired for relatively large areas and the analyses focus on the various approaches to identification, discrimination or classification; (2) exploration of *in situ* acquired hyperspectral data collected under field or laboratory conditions. Here, the focus is on the spectral portion of the hyperspectral cubes, recorded for relatively small objects such as a single plant, branch or leaf, usually with the aim of investigating which portion of the spectrum or even which separate waveband or wavebands contribute most to the spectral separability of different plant species, their condition or chemical constituents. Studies fo-

cused on hyperspectral data at the single plant level show that field or laboratory acquired hyperspectral measurements can significantly contribute to determining a plant’s level of stress (Atzberger & Werner 1998, Smith et al. 2004, Moorthy et al. 2008, Wang & Li 2012). The spectra obtained *in situ* are fundamental in the building of spectral libraries, such as a set of laboratory spectra for various materials. Developing spectral libraries is fundamental to improving the full mapping potential of hyperspectral data (Zomer et al. 2009, Manakos et al. 2010, Nidamanuri & Zbell 2011).

Hyperspectral imaging techniques can identify the optical properties of forest decline and serve to explore the relationship between optical and spectral data to assist in the identification of properties related to the health assessment of a tree (Vogelmann & Rock 1988, Treitz & Howarth 1999). While foliar chlorophyll (as well as carotenoids) concentrations typically decrease when plant stress level increases, additional constituents accumulate within the leaves. Such changes affect leaf spectral properties and provide the possibility of remotely diagnosing a plant’s stress level (Rock et al. 1986, Martin & Aber 1997, Datt 1998, Zarco-Tejada et al. 2004, Malenovský et al. 2006). The reflected radiation of the visible and near infrared portions of the electromagnetic spectrum has proven to be the most important in detecting plant stress (Gitelson et al. 2003). Changes in leaf chlorophyll and water content significantly affect leaf reflectance. Chlorophyll is the most important factor, which affects leaf reflectance in the visible and near-infrared spectra (Carter 1993). The reflectance increases in the 700-1300 nm range due to light scattering from the internal structure of leaves. The differences in reflectance properties between healthy and damaged plants are most observable in the green peak and red edge (Carter et al. 1996, Gitelson et al. 2003). The red edge is where the reflectance curve increases at the margin between the chlorophyll absorption zone in red wavelengths and the light scattering zone in the near-infrared wavelengths. The position of the red edge is considered to be stable across different plant species and ranges from 680 nm to 750 nm (Horler et al. 1983).

In Lithuania, spectral measurements of forest trees in relation to their health status were conducted more than two decades ago using what is now considered an outdated spectral radiometer technology. Only an average reflectance curve for the object being sensed was possible at that time. The research mainly focused on the spectral measurements of needles and branches of Norway spruce (*Picea abies* Karst.) and Scots pine (*Pinus sylvestris* L.) with different levels of crown defoliation. The most effective spectral zones for defoliation assessment

were determined and some methodological solutions for improving the process of spectral measurement were suggested (Repšys 1992). However, since then, no other research on spectral properties of forest trees has been conducted in Lithuania.

This paper describes the initial results of a study using hyperspectral imaging to acquire and use reflectance data at the plant level in Lithuania. The study focuses on the ability of hyperspectral data to discriminate between healthy and stressed Scots pine, Norway spruce and Siberian pine (*Pinus sibirica* Du Tour) trees. Scots pine and Norway spruce are the most common and commercially important tree species in Lithuania. Scots pine stands make up 35.3% and Norway spruce 20.8% of the total forest area (State Forest Service 2011). The introduced Siberian pine, used only in urban areas for landscape design, was also of interest. The objectives include:

- Verifying the significance of spectral differences between healthy and stressed Norway spruce, Scots pine and Siberian pine using hyperspectral imaging techniques.
- Determining the wavebands which best represent the spectral differences between Norway spruce, Scots pine and Siberian pine (stressed and healthy).
- Examining the relationships between the spectral reflectance properties of the needles of Norway spruce, Scots pine and Siberian pine and their chlorophyll content, and determining the wavebands that are most effective in discriminating between the chlorophyll content in the needles of stressed and healthy Norway spruce, Scots pine and Siberian pine.

Materials and Methods

Samples of healthy (no foliar loss or other visible symptoms of tree stress or disease) and stressed Norway spruce (yellowish green needles, foliar loss 66-70%) and Scots pine (yellowish green needles, foliar loss 71-75%) were collected in a 20-year-old mixed Norway spruce-Scots pine stand. A part of this healthy stand portion (~ 0.2 ha) suffered from temporal flooding which consequently resulted in heavily stressed trees with high levels of foliar loss. Samples of healthy (no foliar loss or other visible symptoms of tree stress or disease) and stressed (brownish-green needles, foliar loss 86-90%) Siberian pine of similar age were collected in urban environments since this species is exclusively used for landscape design and is not naturally found in Lithuanian forests.

The middle-upper part of the crown of each tree was easily accessible from the ground and therefore sample branches from the outer crown were cut using a telescopic cutter. Three trees for each species and for each condition were selected for sampling. Nine sample branches were cut from the southern

side of the crown of each tree. A total of 27 samples were collected representing each tree species condition (healthy and stressed). Samples were taken in January 2012. Cut samples were packed into plastic bags with some added snow for sample preservation. Bags were labeled, put into portable cooler bags and transported to the laboratory for immediate spectral measurements.

The scanning process was conducted using a new generation Themis Vision Systems LLC hyperspectral camera VNIR400H (Bay St. Louis, MO, USA). This device was equipped with a highly sensitive VNIR spectrometer capable of covering the spectral range of 400-1000 nm with a sampling interval of 0.6 nm, producing 955 spectral bands. The spatial data of each scanned sample was recorded in a charged-coupled device (CCD) array with a 1392×1000 pixel resolution (pixel size was $6.45 \mu\text{m} \times 6.45 \mu\text{m}$). The camera, using a field of view of 30 degrees, was mounted on a copy stand and was oriented in the nadir position with the lens fixed at 33 cm above the sample. Two 100 W halogen lamps, which can provide stable electro-magnetic radiation in the 400-1000 nm range, were used for sample illumination. The halogen lamps were fixed symmetrically at both sides of the camera's lens and illuminated the sample allowing their light beams to crisscross above the sample. The scanning room was darkened to avoid unrelated spectral signals from ambient light sources.

Hyperspectral image acquisition was executed by locating sample branches only on last year's sprouts and harvesting every needle from them. The needles were then spread on top of a plate painted matt black so that the background plate was fully covered by needles. The spectral response of each needle sample was recorded four times. The background plate was rotated 90 degrees horizontally after every hyperspectral sample to correct for the bidirectional reflectance distribution. These steps were repeated for all samples resulting in raw hyperspectral images of needle samples (four for each separate sample).

Next, the radiance curve was converted to a reflectance curve for each image pixel. Completed target measurements were compared against the ones of a reference panel of known spectral reflectance (Avian Technologies LLC 99% white reference panel). The spectrometer internal current (dark current) was also corrected. The resulting spectra were then smoothed using the Savitzky-Golay filter function with a 4th-order polynomial fit and 25 data points. The steps above were repeated for each hyperspectral image that was then cropped (100×100 pixels).

Finally, four reflectance curves were derived from the four needle sample images and then averaged to construct a single re-

Tab. 1 - Measured average chlorophyll (a + b) content in the needle samples of healthy and stressed trees. (SD): standard deviation.

Tree species	Chlorophyll content (mg/g fw, \pm SD)		Statistical difference (p value)
	Healthy	Stressed	
Norway spruce	3.90 ± 0.06	2.73 ± 0.07	3.09×10^{-09}
Scots pine	2.77 ± 0.06	1.78 ± 0.04	1.40×10^{-09}
Siberian pine	2.19 ± 0.07	1.88 ± 0.04	0.01

fectance curve for each sample. A total of 162 reflectance curves were constructed (54 for each species). Each reflectance curve was treated as a series of numbers (reflectance coefficients) and was used for statistical analyses.

Statistical Analyses

The distribution of the spectral responses at every spectral band was tested for normality using the Shapiro-Wilk test ($\alpha = 0.05$) and the homogeneity of the variance was checked using Levene's test ($\alpha = 0.05$). The spectral data at every spectral band ($p > \alpha$) and for all species investigated were homoscedastic and normally distributed.

Student's *t*-test was applied to compare the spectral responses of both healthy and stressed trees of the same species to determine whether the reflection values of samples of stressed trees were statistically different from healthy trees at every spectral band. The null hypothesis $H_0: \mu_{\text{healthy}} = \mu_{\text{stressed}}$ was compared to the alternative hypothesis $H_1: \mu_{\text{healthy}} \neq \mu_{\text{stressed}}$, where μ was the mean reflectance value of the species compared. Then the hypothesis test was carried out using two sample *t*-tests for all 955 spectral bands ($\alpha = 0.05$). The *t*-test was also used to select the spectral bands that helped distinguish between healthy and stressed trees of corresponding species (spectral bands with the lowest p-values are most separable). The ten bands with the lowest p-values were selected for having high separability power and the spectral band with the lowest p-value was selected for being the most effective at separating healthy and stressed trees.

Principal component analysis (PCA) was employed to search for trends in differences between the healthy and stressed tree needle samples for each tree species. The non-linear iterative partial least squares (NIPALS) algorithm was employed in calculations (Wold 1966, Wold et al. 1987). In this study, principal component analysis was used to compute the contribution of the reflectance coming from each wavelength to the principal components. Wavebands were treated as independent variables. The reflection data of all 54 samples (27 for healthy and 27 for stressed trees) of each tree species were analyzed. The data were pre-processed using unit variance scaling and mean-centering procedures. Component loadings represented

the relative grade to which each variable (waveband) explained the relationship between the component and sampled stress level. If the component covers a significant portion of the overall data variance that is related to the differentiation of stress levels, then the wavebands with highest loadings on that component are well-suited for stress level differentiation. The 20 wavebands with the highest loadings to PC1 and PC2 were selected to display the spectral ranges.

The needle chlorophyll (a + b) content was spectrophotometrically determined in a laboratory by measuring the needle absorbance of ethanol (96.3%) extracts. A Student's *t*-test was used to test for a statistical difference between the measured chlorophyll content of healthy and stressed needle samples (Tab. 1).

The partial least squares regression (PLSR) was used to select the most informative wavelengths with regards to needle chlorophyll content. PLSR is well suited to analyze a large array of related predictor variables (*i.e.*, not truly independent), with a sample size not large enough compared to the number of independent variables (Carrascal et al. 2009, Wold et al. 2001). PLSR models were built independently for the three tree species. The values of one attribute (chlorophyll content of the 54 healthy or stressed needle samples) of the data set were used to represent the dependent variable (Y) and the wavelength reflectance values of the 54 healthy or stressed needle samples represented the independent variables or the predictors (X). The data were pre-processed using unit variance scaling and mean-centering procedures. The R^2Y (multiple correlation coefficient), Q^2 (leave-one-out cross-validation R^2Y) and root mean square error of estimation (RMSEE) were calculated for each model to check the fit and the predictive ability of the models. All three models were also validated using external data sets created by randomly selecting 30 % of samples from initial data sets. The root mean square errors of prediction (RMSEP) were estimated to check the predictive power of the models. The wavebands with variable importance in the projection (VIP) scores > 1 were selected for construction of reduced PLSR models. These models employed the spectral responses of only these bands predictors (X). R^2Y , Q^2 and RMSEP for the re-

duced PLSR models were calculated following the same procedures as stated above.

After comparing both types of the models (involving full range of wavebands and reduced range of wavebands), the ones with higher values of Q^2 and lower values of RMSEP were selected for identification of the wavelengths most sensitive to chlorophyll content. The wavelengths most closely related to chlorophyll content were identified by their VIP scores. The wavelengths that corresponded to the highest values of VIP scores were retained for each tree species. The first 20 bands with the highest VIP scores were retained for their sensitivity in detecting changes in chlorophyll content for each tree species.

Statistical analysis was performed using SPSS version 16.0 (SPSS Inc.) and Simca version 13.0 (Umetrics AB).

Results

Results from the Student's *t*-tests indicated the means of reflectance values of healthy and stressed sample trees were statistically different for the majority of spectral bands. The largest relative spectral differences between healthy and stressed trees were observed for Norway spruce: the means of reflectance values were significantly different (p -values < 0.05) on 884 out of 955 (93%) wavebands, while 767 out of 955 (80%) for Scots pine and 698 out of 955 (73%) for Siberian pine were significantly different. Tab. 2 lists the ten most sensitive bands of the spectral range for separating healthy and stressed trees for each species.

The PCA indicated that the first two principal components explained more than 90% of the variance in the samples of spectra investigated (Tab. 3). Therefore, only the first two principal components (PC1 and PC2) were selected for evaluating the contribution of wavelengths to the separation of healthy and stressed trees (Fig. 1).

The selected spectral ranges and the spectral bands with the highest loadings to PC1 and PC2 are presented in Tab. 3. The principal component analysis was meant to support and validate the results of the Student's *t*-test, but while the results were slightly different, they were not contradictory (Tab. 2

Tab. 2 - Separability of healthy and stressed tree needles (Student's *t*-test).

Tree species	Number of spectrally different (p<0.05) spectral bands (total: 955)	Most informative spectral range for tree stress identification	Most informative wavelength for tree stress identification (smallest p-value)
Norway spruce	884	709.9-715.7 nm	713.1 nm
Scots pine	767	708.6-714.4 nm	711.2 nm
Siberian pine	698	862.3-868.1 nm	864.2 nm

Tab. 3 - Most informative spectral ranges and bands for separation between healthy and stressed tree needles (principal component analysis).

Tree species	Percentage of variability explained by		Spectral range with highest factor loadings to		Wavelength with highest factor loading to	
	PC1	PC2	PC1	PC2	PC1	PC2
Norway spruce	63	33	701.0-713.1 nm	706.1-718.2 nm	707.4 nm	712.5 nm
Scots pine	62	36	706.1-718.2 nm	777.8-790.1 nm	711.8 nm	784.9 nm
Siberian pine	93	6	880.9-893.1 nm	706.1-718.2 nm	884.8 nm	712.5 nm

Tab. 4 - Characteristics of partial least squares regression modelling, including multiple correlation coefficient (R^2Y), leave-one-out cross-validated multiple correlation coefficient (Q^2), root mean square error of estimation (RMSEE), root mean square error of prediction (RMSEP), to predict the chlorophyll content in needles. For each table cell, upper figure refers to the full waveband model, lower figure refers to the reduced waveband model.

Tree species	Number of observations	Number of components	Number of wavebands	R^2Y	Q^2	RMSEE	RMSEP
Norway spruce	54	5	955	0.96	0.95	0.116	0.123
			431	0.96	0.94	0.124	0.136
Scots pine	54	5	955	0.95	0.94	0.115	0.136
			378	0.95	0.93	0.113	0.135
Siberian pine	54	5	955	0.75	0.55	0.067	0.083
			459	0.73	0.58	0.069	0.088

and Tab. 3). Norway spruce and Scots pine wavelengths in the red edge of the spectra were most closely correlated to both PC1 and PC2 (Tab. 3). However, the red edge was only a secondary factor in stress level separation (contributed to PC2 for Siberian pine). A portion of the near infrared spectrum was the primary detector of differences between healthy and stressed Siberian pine trees (largest loadings for PC1). Moreover, principal component analysis revealed a consistent range of wavelengths having the highest factor loadings either to PC1 or to PC2 for all tree species. The 706.1-718.2 nm

spectral interval was strongly involved in the PC2 for Norway spruce and Siberian pine, but for Scots pine, in PC1 (Tab. 3).

The PLSR models involving the full range of predictors indicated a strong potential accuracy to predict the chlorophyll content for Norway spruce and Scots pine, while moderate accuracy for Siberian pine (Tab. 4). VIP scores of these models discovered that 431, 378 and 459 bands out of 955 bands were the most important (VIP score >1) for chlorophyll content prediction for Norway spruce, Scots pine and Siberian pine, respectively. Reducing the number of wave-

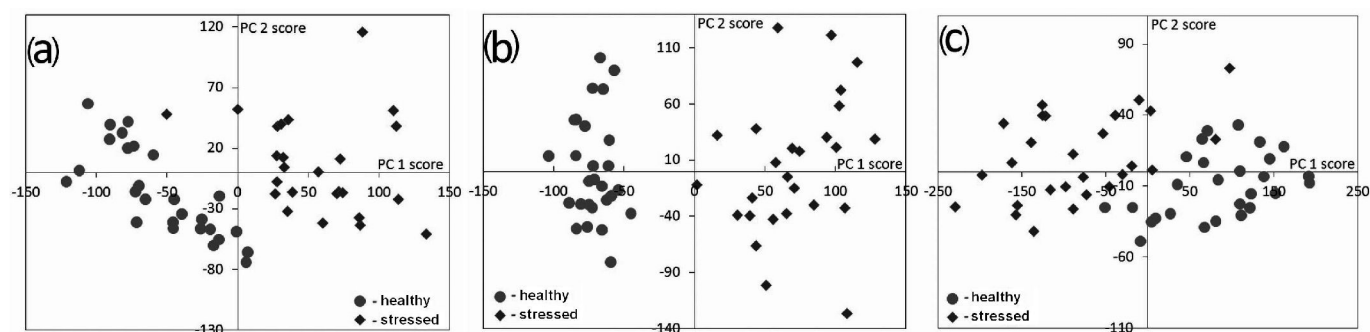


Fig. 1 - Scores of principal component analysis for (a) Norway spruce; (b) Scots pine; (c) Siberian pine.

bands did not improve the accuracy of the models (Tab. 4). PLSR models using the full range of wavebands for detecting which wavelengths are most tightly related to chlorophyll content were most successful. The wavelengths with the most discriminating power (the ones with the highest VIP scores) for distinguishing chlorophyll content in samples of healthy and stressed trees were 715.6, 715.0 and 720.1 nm for Norway spruce, Scots pine and Siberian pine, respectively (Fig. 2). Waveband ranges that were most sensitive to changes in chlorophyll content were very similar for all

three species and generally cover the range of 709.3-722.7 nm.

three species and generally cover the range of 709.3-722.7 nm.

Discussion

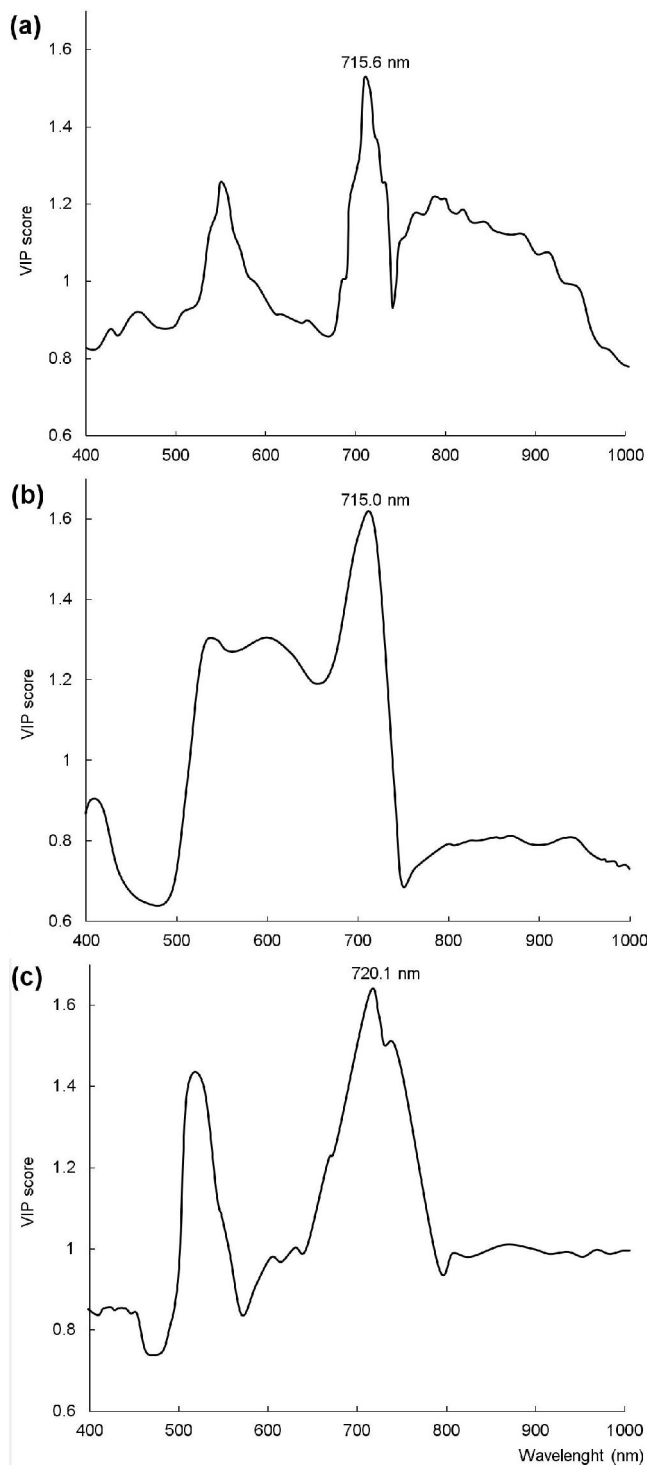
We used the full range of data of all narrow wavebands recorded with a hyperspectral camera. In doing so, we avoided losing information that a single contiguous band might contain regarding the stress level of the studied objects. No effort was made to decrease data redundancy between adjacent bands.

This study revealed that most sensitive spectral ranges for tree stress identification are located at 701.0-715.7 nm for Norway spruce and 706.1-718.2 nm for Scots pine. Also, the partial least squares regression demonstrated that the red edge is the portion of the spectrum where wavelengths are most tightly related to the chlorophyll content. The wavelengths are located at 715.6 nm for Norway spruce, 715.0 nm for Scots pine and 720.1 nm for Siberian pine.

These results are reconcilable with other studies that found the red edge to be most informative in terms of its responsiveness to changes in chlorophyll content caused by plant stress. For example, Carter & Knapp (2001) discovered that an increase in reflectance at 700 nm was the most consequential and most sensitive to plant stress. Their study involved the analysis of the impact of various stressors (such as diseases, insects, dehydration, competition, etc.) on the reflectance in the range of 400-850 nm for different species including loblolly pine (*Pinus taeda* L.), radiate pine (*Pinus radiata* D. Don), sweetgum (*Liquidambar styraciflua* L.), red maple (*Acer rubrum* L.), wild grape (*Vitis rotundifolia* Michx.), switchcane (*Arundinaria gigantea* (Walter) Muhl.) and longleaf pine (*Pinus palustris* Miller). Luther & Carroll (1999) investigated foliar spectral reflectance of balsam fir (*Abies balsamea* (L.) Mill.) and found the reflectance in the red edge at 711 nm was most sensitive to stress. Eitel et al. (2010) analyzed stress-induced variation in chlorophyll concentration for nursery-grown Scots pine seedlings. Accuracy of estimates improved after adding reflectance data in the red edge bands to the initially available spectral reflectance data. Entcheva-Campbell et al. (2004) employed an airborne hyperspectral scanner and found the 673-724 nm range to be the most informative to initial damage of Norway spruce stands in the Czech Republic.

Nevertheless, the most sensitive wavelengths related to stress for Siberian pine were located in the near infrared zone spectra at 862.3-893.1 nm. The principal component analysis, however, proved that the 706.1-718.2 nm interval in the red edge was the second most important factor. This could suggest that changes in the reflectance of the near-infrared range of the spectra were cau-

Fig. 2 - Selection of wavelengths corresponding to the highest value of variable importance in the projection scores of partial least squares regression for: (a) Norway spruce; (b) Scots pine; (c) Siberian pine.



sed by a significant alteration of the inner structures of the Siberian pine needles. This calls for a closer examination of the sample trees. As previously mentioned, sampled trees of stressed Norway spruce and Scots pine were sampled from a forested environment and their foliar loss was 66-70% and 71-75%, respectively. Stressed Siberian pines were sampled from an urban environment and, more importantly, their foliar loss was higher, 86-90%. The Siberian pine results demonstrate the importance of near infrared spectra in the detection of more heavily stressed plants.

In our particular case, the PLS regression results show that the wavelength ranges most sensitive to chlorophyll content were very similar for all three tree species and generally covered the range 709.3-722.7 nm. While most wavelengths detecting chlorophyll content differed depending on the particular species, the disparity was minimal (<6 nm). This complements the findings of Gitelson & Merzlyak (1996) who identified the 700-710 nm range as most sensitive to leaf chlorophyll a concentration for horse chestnut (*Aesculus hippocastanum* L.) and Norway maple (*Acer platanoides* L.). Similarly, Datt (1998) found maximum sensitivity of reflectance to variation in pigment content of leaves of various *Eucalyptus* species in the wavelength regions of 550 nm and 708 nm. Gitelson et al. (2003) discovered that reciprocal reflectance in the spectral ranges of 520 to 550 nm and 695 to 705 nm related closely to the total chlorophyll content in leaves of Norway maple, horse chestnut, wild vine (*Parthenocissus tricuspidata* L.) and common beech (*Fagus sylvatica* L.). A spectral index developed by Malenovský et al. (2006) was proposed to estimate the chlorophyll content of a Norway spruce crown. This index is based on the reflectance continuum removal of the chlorophyll absorption feature between the wavelengths 650-725 nm.

The results of this study suggest that refining the research capabilities of hyperspectral imaging for forest health monitoring in Lithuania could prove beneficial. While the elaboration of a diagnostic tool for remotely detecting stressed plants goes beyond the scope of this study, the technique employed here demonstrated the possibility of distinguishing extreme contrasts of plants stress levels. While this is a limiting factor in the treatment of the study results, the consistency of the results with regards to stress levels suggests that further studies are required to fully understand the relationships between tree stress (different levels of defoliation) and their reflectance properties. For example, more subtle spectral reflectance properties might be revealed when examining trees with lesser differences in stress level or ones with very similar defoliation

but growing on different sites or of different age. With the advent of the new-generation hyperspectral cameras, this is a promising direction for future research.

Conclusions

The study revealed that a strong relationship exists between the spectral reflectance properties of Norway spruce, Scots pine and Siberian pine and their stress status. It also confirmed that the red edge is the most sensitive spectral zone for stress detection in two Lithuanian coniferous tree species, Norway spruce and Scots pine. The importance of near infrared spectra in the detection of heavily stressed coniferous trees should not be underestimated based on our findings for Siberian pine.

The 706.1-718.2 nm spectral interval was a consistently strong stress indicator wavelength for all tree species in this study, although it was of secondary importance in Norway spruce and Siberian pine.

The use of partial least squares regression models suggests that hyperspectral imaging is an effective remote sensing technique for predicting needle chlorophyll content because a strong relationship exists between the needle reflectance spectra of Norway spruce, Scots pine and Siberian pine and their chlorophyll content.

This study demonstrated the strong potential of narrow-band based hyperspectral imaging to detect the differences in reflectance properties of two categories of stress for Norway spruce, Scots pine and Siberian pine. It also set the direction for future research in the use of hyperspectral remote sensing to assess and monitor tree health.

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