

Assessment of ice-storm damage in forests using remote sensing

Svetoslav Anev 

Department of Dendrology, Faculty of Forestry, University of Forestry, 10 Kliment Ohridski Blvd., 1797 Sofia, Bulgaria. E-mail: svetoslav.anev@ltu.bg

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Abstract

Extreme weather events such as ice-storms increasingly impact forest ecosystems, yet effective methods for assessing their damage remain limited. This study aims to compare the applicability of three vegetation indices based on imagery obtained from Sentinel-2 satellites in assessing damage from large-scale forest disturbance caused by an ice-storm in the Western Stara Planina Mts. The rate of damages was assessed using the temporal comparison in the Normalized Difference Vegetation Index (NDVI), Plant Phenology Index (PPI), and Leaf Area Index (LAI) between August 2020 and August 2021. The results showed that NDVI is less sensitive for canopy changes in complex phytocoenosis such as forests. Due to the forest's understory phenology, PPI has a low relation with canopy destruction and indexes false positive changes between 2020 and 2021. LAI reduction was closely related to terrain assessment results, but there was still an index increase in stands with high damage values established during field assessments. A significant challenge in forest disturbance damage analysis based on changes in vegetation indices remains the objectivity of the field assessments used as a control for comparing the applicability of indices. Quality and quantitative assessment of disturbance impacts on forests using remote sensing requires precise ground-based data and integration of this information with vegetation indices. Due to partial crown destruction in some affected trees, remotely sensed indices incorporating canopy depth are well-suited for assessing damage caused by natural forest disturbances.

Key words: Leaf Area Index, Normalized Difference Vegetation Index, Plant Phenology Index.

Introduction

Natural disturbances are part of forest dynamics (Grebner et al. 2012), but unlike micro-disturbances, which diversify the functions, structure, and development of stands (Oliver and Larson 1996), large-scale natural disturbances lead to rapid change in the forest environment. Ac-

cording to Voller and Harrison (2011), the scale of a natural disturbance can vary significantly, depending on the nature of the event that causes it, as well as on the orography of the terrain and the structure of the forest. The period between two large-scale natural disturbances is often shorter than the potential lifespan of late-successional species (Oliver and Lar-

son 1996). Therefore, large-scale natural disturbances free up space for the accommodation of pioneer plant species, restarting succession and changing the species composition of forests.

Forest ecosystems are often represented by a mosaic of stands that vary in age, composition, structure, and functionality. Their dynamic appearance is formed primarily by disturbances, which can be natural or anthropogenic. Lazarov et al. (2009) point out that periodic natural disturbances are a crucial factor in the life cycle of forest ecosystems and maintain their diversity and functions over a long period. Wind, snow or ice, torrential rains and floods, fires, avalanches, etc., cause natural disturbances. The frequency and intensity of ice-storms are expected to increase with climate change, leading to more frequent and severe damages. Ice-storm damage can range from minor twig breakage to complete trunk break or uprooting (Guo and Xue 2012), depending on the spatial and temporal extent of the damaging event (Olthof et al. 2004). This structural damage can significantly alter forest dynamics and recovery processes (Cao et al. 2020). Ice-storm damage to the forest canopy affects understory light conditions, influencing species regeneration and forest dynamics. It also impacts soil, litter, disease fungi, and wildlife (Guo and Xue 2012).

Damage assessment after a natural disturbance is still labour-intensive and requires solid human resources. It is subjective mainly because primitive scales and criteria are used. Moreover, assessors often vary due to the large scale of the affected territories, which could contribute to an increase in errors.

Several methods and indices can be employed to assess ice-storm forest damages using vegetation indices, primarily

leveraging remote sensing data (Frolking et al. 2009). According to Lechner et al. (2020), remote sensing can demonstrate high potential in monitoring forest changes over long periods or comparing different sites. Remote sensing has been used in a diverse range of forest ecology and management applications from mapping invasive species to monitoring land-cover changes, such as habitat fragmentation, to estimating biophysical and biochemical properties of forests. Some crucial advantages of remote monitoring methods for forest ecosystems are related to the ability to capture a comprehensive picture of the current state of forests, track this state over time based on periodic surveys of the same territory, digitize the data, and link it geographically (Lechner et al. 2020). Satellite remote sensing is emerging as an efficient tool for monitoring vegetation dynamics due to natural disturbances, using frequent observation, wide coverage and easy data collection (Lechner et al. 2020, Zhao et al. 2024a). According to Asenova and Angelov (2022), a remote sensing assessment can save time and effort, use objective criteria, and allow the analysis of natural disturbances' principal risks and prerequisites. Forests have a specific absorption capacity for red and infrared light (Treitz and Howarth 1999), so it is possible to assess the damage based on satellite images taken in these light ranges. The relationship between remotely sensed vegetation indices and forest damage caused by natural disturbances is still hardly studied. Factors such as mixed species complexes, vertical structure, topography, time of day and year, vegetation phenology, weather conditions, moisture, and stress, complicate computer-based analysis procedures by increasing spectral variance and reducing the spectral separability of classes (Pitt et

al. 1997). This can add variations in tracking long-term trends and cause false positive or negative signals in forest dynamics. The atmosphere varying transmittance to light can also distort the results of long-term monitoring. Even if we exclude clouds with some modern approaches, causes of inaccuracies, such as humidity and dustiness of the atmosphere, remain more difficult to identify and compensate for (Kaufman et al. 1997). The diversity of reasons for change in forests complicates identifying and analysing disturbances. Human activity in forest management leads to significant changes in their natural dynamics and can enhance or mask some natural processes (Barbero et al. 1990). Studies that require detailed information on smaller plants (<0.5 m tall) and/or individual or rare plant species are unlikely to be supported by current remote sensing technologies (Pitt et al. 1997).

One of the most commonly used vegetation indices in environmental studies determined from satellite images is the Normalized Difference Vegetation Index (NDVI) proposed by Rouse et al. (1974), which is calculated using images of reflected light in the red (RED) and infrared (NIR) parts of the light spectrum (Pettorelli et al. 2005):

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (1)$$

The equation (1) is based on the fact that infrared light is reflected more intensely by plants' leaves with more hydrated and healthy cell walls. At the same time, leaves with more chlorophyll reflect less red light. Therefore, higher NDVI values show a higher life potential and a better ability to absorb the carbon of the vegetation (Tucker et al. 1991).

Several authors point to the direct relationship between NDVI and forest productivity (Sellers et al. 1992, Vourlitis et

al. 2003, Bailey et al. 2004). However, NDVI has one significant drawback when studying vegetation dynamics in forest areas. After quickly reaching the maximum value for the season, NDVI remains high for an extended period because it is less sensitive to fluctuations in water content and chlorophyll in summer, especially in compact forests (Huete et al. 2002). For this reason, Grabska-Szwagrzyk and Ty mińska-Czabańska (2024) recommend for monitoring in forests to use indices that reflect in more detail the state of the leaf apparatus during individual months of the year, such as the Enhanced Vegetation Index (EVI), calculated by equation (2).

$$EVI = 2.5 \cdot \frac{NIR - RED}{NIR + 6 \cdot RED - 7.5 \cdot BLUE + 1} \quad (2)$$

By using the blue channel in the calculation of EVI, the background influence of soil and particles in the atmosphere is reduced. Blue light, on the other hand, is scattered strongly in the atmosphere (Ahrens and Henson 2015). According to Jin and Eklundh (2014), with static sensors such as those on the Sentinel-2 satellites, there is often considerable variation and a decrease in the accuracy of the determined index, especially at higher latitudes. The authors propose a new approach for calculating a vegetation index based on biophysical laws such as the diffuse reflectance law of Hapke (2012). Based on Buschmann and Nagel (1993) assumptions, that the logarithm of the ratio between NIR and RED shows a much stronger relationship with chlorophyll content, and considering the advantages of normalized indices, Jin and Eklundh (2014) formulated a Plant Phenology Index (PPI).

$$PPI = -K \cdot \ln \left(\frac{DVI_{MAX} - DVI}{DVI_{MAX} - DVI_{Soil}} \right) \quad (3)$$

In the PPI equation (3), DVI (Differ-

ence Vegetation Index) is the difference between NIR and red reflectance; DVI_{MAX} is the maximum DVI value for the most extended possible period, and DVI_{Soil} is the soil DVI, which is used as the minimum PPI correction value. Factor K is a PPI gain factor that depends on the canopy's density, the leaves' light transmission, the inclination of the leaves to the horizontal, and the angle of incidence of the sun's rays (Jin and Eklundh 2014). One of the most significant advantages of PPI as a biophysical index is its strong correlation with the Leaf Area Index (LAI), which is widely used in forest research because it shows a strong relationship with forest productivity. LAI is broadly defined as the amount of leaf area (m^2) in a canopy per unit ground area (m^2) (Watson 1947). It determines the size of the interface for exchange of energy (including radiation) and mass between the canopy and the atmosphere. LAI is an intrinsic canopy primary variable that is independent of observation conditions (WEKEO 2023). Weiss et al. (2004) described the methodology for deriving LAI from Sentinel-2 products. It's based on INRA's 5-level neural network (Fernandes et al. 2014). The relationship between LAI and PPI is linear, unlike the non-linear relationship of the widely used NDVI and EVI, whose levels saturate as LAI increases above 2–3 $m^2 \cdot m^{-2}$.

A change between the spectral indices of pre-disturbance and post-disturbance images is a widely used approach to assess rate of damages (Miller and Yool 2002, Olthof et al. 2004, Brewer et al. 2005, Röder et al. 2008, Sharma et al. 2022, Zhao et al. 2024b). Differencing can result in a measure of absolute or relative change correlated to the pre-disturbance image. A significant change in live biomass will be measured in a pixel experiencing complete mortality that contained a

large amount of photosynthetically active vegetation in the pre-disturbance image (Miller and Yool 2002). Damage classification typically requires assignment of a continuous damage measure into discrete damage classes. A limitation of the classification approach is that the boundaries between damage classes are artificial and subjective (Olthof et al. 2004).

The approach of using the difference between pre- and post-disruption images to assess damage from natural disturbances has the potential to save time and effort in field surveys. Remotely sensed indices can help differentiate areas of low or medium damage from areas of severe damage. Such classification methods can provide regional damage maps more objectively than point-based visual estimates and aid in identifying areas of severe damage where management intervention may be advantageous (Olthof et al. 2004). The three studied vegetation indices have different advantages when used as criteria for remote assessment. NDVI is easy to calculate (Pettorelli 2013), and the literature provides numerous examples of its use for similar purposes (Nedkov et al. 2020, Pettorelli et al. 2005, Sharma et al. 2022). The use of PPI makes the assessment significantly more complex, as this index responds not only to changes in the main forest stand but also to changes in the vegetation community's lower biotic horizons (Jin and Eklundh 2014, Anev 2023). LAI is most closely related to forest productivity and records damage in a way that is closest to the visual assessment method (Clark et al. 2008, Fernandes et al. 2014). However, each index also has its drawbacks, which became apparent from the study. NDVI quickly saturates to relatively high values, making it less sensitive to minor damage (Gamon et al. 1995).

A significant problem when comparing vegetation indices from two years is the interannual variation of the index due to specific meteorological conditions in individual years. Establishing a threshold for damage assessment involves comparing pre- and post-disturbance vegetation index values, which can be done by calculating the standard deviation of pixels in undamaged areas and setting a threshold based on this deviation (Wu et al. 2016). Myneni et al. (1998) observed 10% interannual variation of NDVI in Alaska over nine years (1981–1990). For the same period, Tucker et al. (1991) point out that the coefficient of variation of NDVI above 0.25 corresponds well to the Sahel. Xiao-Bing et al. (2003) established approximately 20% interannual variation of NDVI over 17 years (1983–1999) for the temperate steppe in Northern China. Rowhani et al. (2011) showed that temperate broadleaf forests experienced 5.63% interannual variations in EVI from 2000 to 2006 but also pointed out that around 14 % of the global vegetation experienced more than 20% of interannual variability in land surface attributes relative to the median year over the six years. Cheng et al. (2024) found that China's vegetation status (based on EVI) exhibits a notable intra-annual variation pattern of high in summer and low in winter, and the changes are more pronounced in the northern regions than in the southern regions. The interannual dynamics of vegetation indices in forests, especially those of a biophysical nature such as PPI and LAI, are often due to interannual fluctuations in phenological dynamics related to cumulative temperatures, the main tree species, the stage of development, the structure of the forest, etc. (Peaucelle et al. 2019, Olthof et al. 2004). Anev (2023) found that for 2017–2023, the PPI in 'Petrohan' Training and

Experimental Forest Range varied (based on the standard deviation) from 1 % in December-January, to 23 % in June-July, and the average for the year was 10 %. Wu et al. (2016) recommended the same values for deviation from the mean of NDVI and EVI as a threshold to identify damaged areas.

In Bulgaria, vegetation indices are barely entering the study of ecosystems. At this stage, the NDVI index finds a broader application in precision agriculture. It is used to assess the production potential of crops and the need for fertilisation and watering (Oliver 2014, Hristov et al. 2020). Attempts are being made to use data from vegetation indices to assess the risk of calamities in forests (Stoyanova et al. 2018) or forest fires (Nedkov et al. 2020), which is regrettably not made by plant physiologists or foresters. There is still a broad scope for using vegetation indices to analyse forest dynamics, management activities, and decision-making.

This study aims to compare the applicability of three vegetation indices based on satellite imagery in assessing damage from large-scale forest disturbance caused by an ice-storm in the Western Stara Planina Mts.

Object and Methods

Object

'Petrohan' is located on the northern macro slope of Western Stara Planina Mountains. The territory is 7290.4 ha. The average altitude is 958 m, varying from 319 m to 1794 m (Fig. 1).

According to the climate norms for the last reference period (1991–2000), the average annual temperature is 8.0 °C. It varies from 3.5 °C in the highest altitude

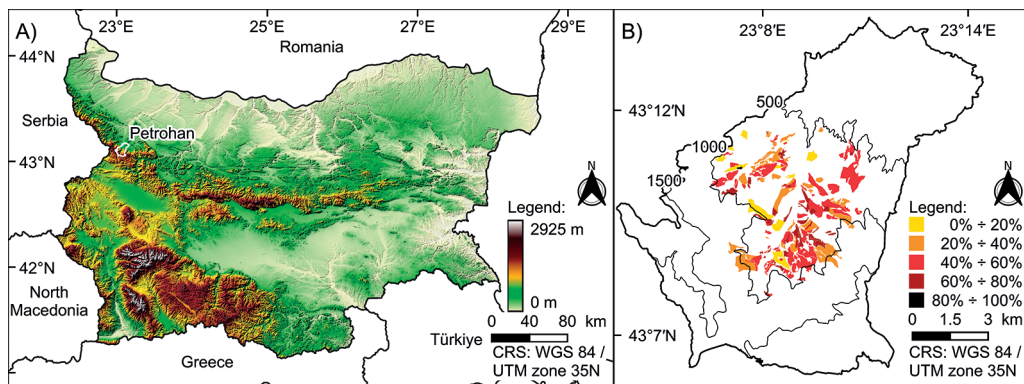


Fig. 1. Location of the study object (A) and damage assessed in the field (B).

to 11.7 °C in the lowest. Precipitation varies significantly across the region. The average annual amount is about 1200 mm, but in individual years, it can reach over 1500 mm; in other years, it can drop to 850 mm (Marinova and Bocheva 2023). With climate change, extreme events causing forest damage are becoming more frequent. An extreme climate event is associated with the forest damages examined in this study. On the evening of January 7, 2021, precipitation began in the Western Stara Planina region. At the same time, air temperatures at 900 m a.s.l. remaining above freezing (2.7 °C). By the night of January 8, temperatures fell below 0 °C and remained negative until January 13. During this period (January 8 to 06 h on January 13), the mean air temperature at 900 m was -3.14 °C, with total precipitation reaching 44.3 L·m⁻². Persistent snow accumulation on tree crowns culminated in widespread structural damage on the morning of January 13, including uprooted trees and breakage of stems and crown segments, opening wounds for various pathogens.

The damages were described in 199 stands over about two years, which required daily, intensive field visits by forest rangers. The extent of damages, includ-

ing the area and rate of the affected part of the stands, were determined during the field assessments on a visible scale in percent (Fig. 1B). More objective and spatially explicit approaches to assessing ice-storm damage were needed to help understand the risk factors and effects of the storm and to provide a baseline for monitoring forest recovery.

Data collection, preparation, and analysis

Archived database, such as Sentinel-2 satellite images from the European Space Agency's Copernicus program, may enable pre- and post-storm change analysis. The High-Resolution Vegetation Phenology and Productivity (HR-VPP) Database from the Copernicus Land Monitoring Service (WEkEO 2023) was used to calculate the changes of three vegetation indices (VI) for the period 2020 ÷ 2021. The VI database comprises three daily vegetation indices: Plant Phenology Index, Normalized Difference Vegetation Index, and Leaf Area Index, as well as quality information that is part of the Copernicus Land Monitoring Service (CLMS) HR-VPP product suite. Images captured by the S2A Sentinel-2 satellite on 31.08.2020

and 16.08.2021 were used to calculate relative changes of PPI, NDVI and LAI for each 'Petrohan' stand.

Data processing was carried out in the following sequence:

1. The polygons of the stands in 'Petrohan' were downloaded from the national forest inventory database (<https://maps.iag.bg/>). Out of a total of 2506 polygons, only those 2093 that are closed canopy forests were filtered.

2. The images S2A_T34TFN-010m_V101 for the PPI, NDVI and LAI indices for the dates 31.08.2020 and 16.08.2021 were downloaded from the site of Wekeo (2023);

3. In QGIS (v. 3.36.1-Maidenhead), the images were clipped along forest stands polygons with the 'clip raster by mask layer' plugin (GDAL, v. 3.8.4).

4. The relative differences in vegetation indices were calculated using the built-in raster calculator by equation (4).

$$\Delta VI_{20 \div 21} = \frac{VI_{20} - VI_{21}}{VI_{20}} \cdot 100, \quad (4)$$

where: $\Delta VI_{20 \div 21}$ is relative changes of NDVI, PPI, and LAI between 2020 and 2021; VI_{21} is value of index' pixel from image of 16.08.2021; VI_{20} is value of index' pixel from image of 31.08.2020.

5. Using the built-in 'zonal statistics' tool, the arithmetic mean values, standard deviations, and number of pixels of the relative difference images $\Delta NDVI_{20 \div 21}$, $\Delta PPI_{20 \div 21}$, and $\Delta LAI_{20 \div 21}$ were calculated only for those 199 described with damages in a field assessment forests polygons.

6. Using the 'join attributes by field value' add-on, the data were merged into one attribute table and this table was exported in CSV format for subsequent analysis in MS Excel.

7. In MS Excel, some statistical parameters (Spearman rank correlation coefficient,

root mean square error, and covariance) were calculated between $\Delta VI_{20 \div 21}$ and observed in terrain assessment damages.

Results

The change in vegetation indices, determined through relative difference images from 2021 and 2020, shows that the negative changes in indices were concentrated in the altitude range of 500 to 1100 m. In relative terms, among the examined indices, NDVI was changed the least – the average raster value was -3.88 %, meaning a slightly higher average NDVI in 2021 compared to 2020. More than 81 % of the pixels in the $\Delta NDVI_{20 \div 21}$ image have negative values close to zero. Among the positive pixels, 92.7 % fall within the range (0 % ÷ 20 %], 6.5 % have values in the range (20 % ÷ 40 %], 0.8 % have values in the range (40 % ÷ 60 %], and only 0.05 % (65 pixels) have values above 60 %. The average value of $\Delta NDVI_{20 \div 21}$ at the stand level for the 199 stands with damage described during the field assessment is 7.21 ± 0.36 %, with a highest value of 26.37 %. However, in 193 (97 %) of these stands, a minimal increase in $\Delta NDVI_{20 \div 21}$ was recorded within the range (0% ÷ 20%], while only six stands (3 %) show an increase in NDVI within the following range (20% ÷ 40%]. There were no stands with an increase in $\Delta NDVI_{20 \div 21}$ above 40 %. The Spearman rank correlation coefficient between the field-described damage and the recorded reduction in NDVI from 2020 to 2021 is 0.253 (P -value < 0.001), with a Root Mean Square Error (RMSE) of 47.4. The covariance between the two series was positive, however, it was only 19.6 (Fig. 2A).

Unlike NDVI, $\Delta PPI_{20 \div 21}$ image was

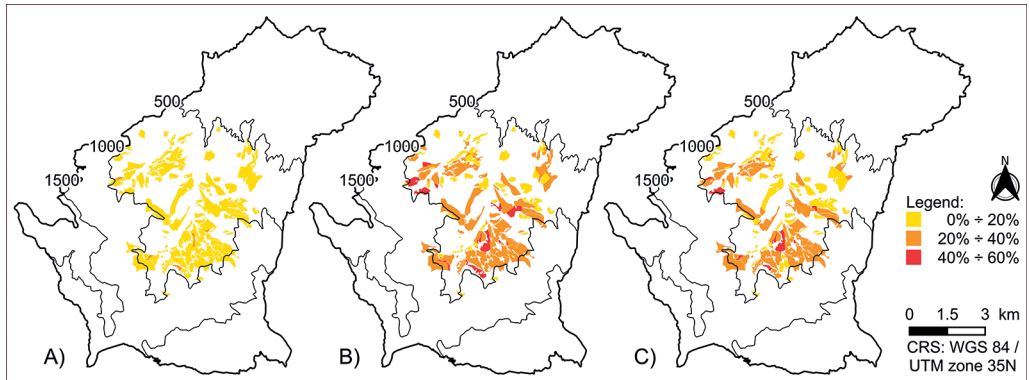


Fig. 2. ΔVI_{20+21} for 199 stands with damage assessed in the field. A) $\Delta NDVI_{20+21}$; B) ΔPPI_{20+21} ; C) ΔLAI_{20+21} .

much more saturated with negative pixels. Despite this, the average raster value was -61.9 %, indicating significantly higher PPI levels in 2021 compared to 2020. A total of 82.4 % of the pixels in the ΔPPI_{20+21} image have negative values. Among the pixels with positive values, 47.3 % fall within the range (0 % ÷ 20 %], 30.9 % have values in the range (20 % ÷ 40 %], 16 % have values in the range (40 % ÷ 60 %], 5.2 % have values in the range (60 % ÷ 80 %], and 0.7 % (773 pixels) have values above 80 %. The average value of ΔPPI_{20+21} at the stand level for the 199 stands with damage described during the field assessment is 25.1 %, which was higher among studied indices. In 71 (35.7 %) ΔPPI_{20+21} fall within the range (0 % ÷ 20 %], 106 (53.3 %) were in the range (20 % ÷ 40 %], and 22 (11.0 %) were in the range (40 % ÷ 60 %]. Spearman rank correlation coefficient between the field-described damage and ΔPPI_{20+21} was 0.742 (P -value < 0.001), Root Mean Square Error (RMSE) is 31.9, and the covariance was the highest (52.3) among the studied indices. (Fig. 2B).

ΔLAI_{20+21} image was more saturated with positive pixels than $\Delta NDVI_{20+21}$ but less saturated than ΔPPI_{20+21} . The average raster value was -27.1 %, confirming

the trend for forests in 'Petrohan' to have higher indices levels in 2021 than in 2020. Among the pixels with positive values, 58.7 % fall within the range (0 % ÷ 20 %], 27.5 % have values in the range (20 % ÷ 40 %], 10.9 % have values in the range (40 % ÷ 60 %], 2.6 % have values in the range (60 % ÷ 80 %], and 0.2 % (277 pixels) has a value above 80 %. The average value of ΔLAI_{20+21} at the stand level for the 199 stands with damage described during the field assessment is 20.9 %. However, in 107 (53.8 %) stands ΔLAI_{20+21} fall within the range (0 % ÷ 20 %], 79 (39.7 %) stands were in the range (20 % ÷ 40 %], and 13 (6.5 %) were in the range (40 % ÷ 60 %]. Spearman rank correlation coefficient between the field-described damage and ΔLAI_{20+21} was the highest – 0.937 (P -value < 0.001), Root Mean Square Error (RMSE) was the lowest – 30.2, and the covariance was 57.3 (Fig. 2C).

Discussion

Although NDVI is the most commonly used vegetation index in assessing vegetation cover conditions, it is insufficiently sensitive for evaluating natural distur-

bances. On the one hand, as pointed out by some authors (Pettorelli et al. 2005, Jin and Eklundh 2014, Cheng et al. 2024), this is due to its rapid saturation in spring and the maintenance of relatively high values for an extended period during the summer and even into autumn. On the other hand, the simple calculation mechanism of NDVI, based on the use of IR light that reacts to the moisture content of objects (Pettorelli 2013), results in falsely high values for non-vegetated objects with high moisture, such as wet soils (Yang et al. 2019). The minimal number of stands, categorized only in the weakest damage category, indicates that NDVI is low sensitive and unsuitable for assessing damage from natural disturbances, especially in complex vegetation communities such as forests.

Plant Phenological Index (PPI) was designed to include a biophysical component (Jin and Eklundh 2014) that accounts for canopy density, making it significantly more suitable for assessing the condition of forest communities (Junttila et al. 2023). Furthermore, PPI accounts for soil and snow reflectance (Smets et al. 2022), making it helpful in evaluating areas stripped of vegetation (Yang et al. 2019), as observed after large-scale natural disturbances. On the other hand, PPI is based on the degree of greening, relying on a simple difference between the reflectance of red and IR light (Jin and Eklundh 2014). This means that regardless of damage to the main canopy layer, which formed the canopy cover, if the lower biotic horizons of the vegetation community (such as the shrub and grass horizons) contain green leaves, PPI will remain high or may even exceed the pre-disturbance value (Smets et al. 2022). A serious risk of mistakes also exists because PPI is strongly influenced by leaf aging (Jin and Eklundh 2014), which is only partially

related to the observation date but is much more affected by the complex hydro-thermal conditions preceding the observation (Zhao et al. 2016). In the case of damage assessment from an ice-storm, these shortcomings are evident from the large number of stands with $\Delta PPI_{20 \times 21} < 0\%$, including those with reported 60 % damage during field assessment. Thus, despite the high covariance, the correlation coefficient between $\Delta PPI_{20 \times 21}$ and field-described damages remains the lowest, and RMSE is the highest among the indices studied.

The established changes in LAI most closely match the field-determined damage. The highest correlation and covariation among studied indices are probably because the crowns and canopy, from which LAI depends mostly, were evaluated during the terrain assessment. LAI indirectly accounts for canopy density, which helps to index even minor damage, such as broken crowns or snapped individual branches. At the same time, Leaf Area Index is calculated based on the fraction of photosynthetically active radiation absorbed by the terrain (Fernandes et al. 2014). Excluding IR light when determining LAI helps to some extent reduce noise caused by the water content of objects (Weiss et al. 2004).

Conclusions

The three indices considered have specific features that make them suitable for various aspects of forest monitoring. We confirmed that NDVI is insufficiently sensitive for evaluating natural disturbances in forests. Even with larger-scale disturbances, such as the ice-storm assessed in the present study, NDVI changes by about one-quarter, complicating damage severity differentiation. In cases of mod-

erate damage, where only branches are broken or even single crowns are affected, PPI tends to increase because the altered light regime in the affected stand favours the phenology of the understory. Earlier unfolding and a more extended vegetation period of the understory lead to many false positive ΔPPI_{20+21} values. Our results showed that among the studied vegetation indices, LAI is the most suitable for assessing damage caused by natural disturbances in forests. A significant challenge in damage analysis based on changes in vegetation indices remains the objectivity of the reference data used for comparison, namely field assessments conducted by different evaluators, often based on subjective criteria and scales and carried out over an extended period. Quality and quantitative assessment of disturbance impacts on forests with remote sensing requires precision ground-based data and linking this information to vegetation indices. Due to partial crown destruction in some of the affected trees, remotely sensed indices that include the canopy depth are suitable for assessing damage from natural forest disturbances.

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