

Correction

Correction: Miletić et al. Quantifying Forest Cover Loss as a Response to Drought and Dieback of Norway Spruce and Evaluating Sensitivity of Various Vegetation Indices Using Remote Sensing. *Forests* 2024, 15, 662

Boban R. Miletić ^{1,*} , Bratislav Matović ² , Saša Orlović ², Marko Gutalj ¹, Todor Đorem ¹, Goran Marinković ³ , Srđan Simović ⁴, Mirko Dugalić ⁴ and Dejan B. Stojanović ² 

- ¹ Department of Forestry, Faculty of Agriculture, University of East Sarajevo, Vuka Karadžića 30, 71123 Istočno Sarajevo, Republic of Srpska, Bosnia and Herzegovina; marko.gutalj@pof.ues.rs.ba (M.G.); todor.djorem@pof.ues.rs.ba (T.Đ.)
- ² Institute of Lowland Forestry and Environment, University of Novi Sad, Antona Čehova 13D, 21102 Novi Sad, Serbia; bratislav.matovic@uns.ac.rs (B.M.); sasao@uns.ac.rs (S.O.); dejan.stojanovic@uns.ac.rs (D.B.S.)
- ³ Department of Civil Engineering and Geodesy, Faculty of Technical Sciences, University of Novi Sad, Trg Dositeja Obradovića 6, 21000 Novi Sad, Serbia; goranmarinkovic@uns.ac.rs
- ⁴ Public Enterprise National Park “Kopaonik”, Suvo Rudište bb, 36354 Kopaonik, Serbia; srkissimovic@gmail.com (S.S.)
- * Correspondence: boban.miletic@pof.ues.rs.ba



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In the original publication [1], several references were not cited and were misreferred in Section “1. Introduction”, paragraph number 4, as Refs. [42–45].

These citations have been removed, and new ones, Refs. [49–52], have been inserted and should read:

“In the last decade, such events have often been studied with the use of remote sensing-produced vegetation indices (VIs) to provide precise explanations of spatial-temporal trends of drought effects [4,38–41], pest outbreaks [42–48], and other forest disturbances [49–52].”

New Refs. are as follows:

49. Jin, S.; Sader, S.A. Comparison of time series tasseled cap wetness and the normalized difference moisture index in detecting forest disturbances. *Remote Sens. Environ.* **2005**, *94*, 364–372. <https://doi.org/10.1016/j.rse.2004.10.012>.

50. Nath, B.; Acharjee, S. Forest Cover Change Detection using Normalized Difference Vegetation Index (NDVI). A Study of Reingkhongkine Lake’s Adjoining Areas, Rangamati, Bangladesh. *Indian Cartogr.* **2013**, *33*, 348–353.

51. Zhang, K.; Thapa, B.; Ross, M.; Gann, D. Remote sensing of seasonal changes and disturbances in mangrove forest: A case study from South Florida. *Ecosphere* **2016**, *7*, e01366. <https://doi.org/10.1002/ecs2.1366>.

52. Schultz, M.; Clevers, J.G.P.W.; Carter, S.; Verbesselt, J.; Avitabile, V.; Quang, H.V.; Herold, M. Performance of vegetation indices from Landsat time series in deforestation monitoring. *Int. J. Appl. Earth Obs. Geoinf.* **2016**, *52*, 318–327. <https://doi.org/10.1016/j.jag.2016.06.020>.

In the original publication [1], many citations and reference numbers were shifted. Several reference citations did not correspond to the reference numbers next to them. After inserting new references, corrections were made in several sections and subsections, as well as in Table 3.

References were updated in the following sections and subsections:

In Section 1. starting from Paragraph 4, all the references were updated from the following:

By utilizing the spectral reflectance characteristics of plants, gathered via various imaging techniques, and combining reflectance from specific spectral wavelengths (bands) [49],

VIs make the large-scale analysis of forest vegetation inexpensive and reliable. As proven by many studies [43,45,50–53], VIs have also been found to be very sensitive in forecasting conifer health status, as they can signal drought stress and pest outbreaks, facilitating timely interventions in forest management and thus reducing the adverse effects of such disturbances. Therefore, the non-invasive approach and efficiency of VIs in forest health monitoring, which is made possible using high temporal frequency and spatially explicit satellite data, can provide insights into current and future forest health status over large-scale forested areas. For example, various VIs have been applied in forest health monitoring, and the most common ones are the Normalized Difference Vegetation Index (NDVI), the Soil-Adjusted Vegetation Index (SAVI), the Transformed Vegetation Index (TVI), the Normalized Difference Moisture Index (NDMI), the Disease Water Stress Index (DSWI), Tasseled Cap Wetness (TCW), and Tasseled Cap Greenness (TCG) [38,39,45–48,50,53–56]. Despite their high accuracy, other conventional methods require constant, time-consuming, and cost-ineffective monitoring service, thus indicating the utter importance and innovativeness of remote sensing-produced VIs in monitoring forest health status over large-scale forested areas. Regardless, the application of VIs has not demonstrated any significant use in forest-themed studies in Serbia. Past studies in Serbia have mainly focused on spatial and temporal forest cover mapping [57–63], mapping of illegal logging effects [64,65], and mapping of wildfire effects [66,67]. An exception is the research of Jovanović and Milanović [68], in which the health status of beech forests was evaluated using VIs, more precisely the NDVI. As past studies in Serbia did not provide precise answers for drought-induced causes or other causes of deforestation, in this research, we aim to fill those gaps by quantifying, spatially and temporally, forest cover loss and evaluating the sensitivity of several VIs in detecting responses to drought and predicting the dieback of Norway spruce due to long-lasting drought effects in the Kopaonik NP.

To the following:

By utilizing the spectral reflectance characteristics of plants, gathered via various imaging techniques, and combining reflectance from specific spectral wavelengths (bands) [53], VIs make the large-scale analysis of forest vegetation inexpensive and reliable. As proven by many studies [43,45,54–57], VIs have also been found to be very sensitive in forecasting conifer health status, as they can signal drought stress and pest outbreaks, facilitating timely interventions in forest management and thus reducing the adverse effects of such disturbances. Therefore, the non-invasive approach and efficiency of VIs in forest health monitoring, which is made possible using high temporal frequency and spatially explicit satellite data, can provide insights into current and future forest health status over large-scale forested areas. For example, various VIs have been applied in forest health monitoring, and the most common ones are the Normalized Difference Vegetation Index (NDVI), the Soil-Adjusted Vegetation Index (SAVI), the Transformed Vegetation Index (TVI), the Normalized Difference Moisture Index (NDMI), the Disease Water Stress Index (DSWI), Tasseled Cap Wetness (TCW), and Tasseled Cap Greenness (TCG) [38,39,45–48,54,57–60]. Despite their high accuracy, other conventional methods require constant, time-consuming, and cost-ineffective monitoring service, thus indicating the utter importance and innovativeness of remote sensing-produced VIs in monitoring forest health status over large-scale forested areas. Regardless, the application of VIs has not demonstrated any significant use in forest-themed studies in Serbia. Past studies in Serbia have mainly focused on spatial and temporal forest cover mapping [61–67], mapping of illegal logging effects [68,69], and mapping of wildfire effects [70,71]. An exception is the research of Jovanović and Milanović [72], in which the health status of beech forests was evaluated using VIs, more precisely the NDVI. As past studies in Serbia did not provide precise answers for drought-induced causes or other causes of deforestation, in this research, we aim to fill those gaps by quantifying, spatially and temporally, forest cover loss and evaluating the sensitivity of several VIs in detecting responses to drought and predicting the dieback of Norway spruce due to long-lasting drought effects in the Kopaonik NP.

In Section 2, *Subsections 2.1–2.5*, all the references were updated from the following:

2.1. Study Area

The study area (Figure 1) is situated within the Kopaonik National Park (NP) in southern Serbia, which gained its current status in the year 1981 due to its biodiversity, rich flora and fauna, and great cultural and historical importance [69,70]. The park stretches across 11,969.04 ha of land in low-populated areas of municipalities Brus and Raška, mainly on mountain Kopaonik (2017 m.a.s.l) [71,72], of which 7427.24 ha is covered by forests [73]. Higher parts of the mountain are mainly covered with pure or mixed conifer stands of Norway spruce (*Picea abies* (L.) Karst.) and Silver fir (*Abies alba* (L.) Mill.), with or without European beech (*Fagus sylvatica* L.), which in addition to Austrian pine (*Pinus nigra* Arn.) and oak species (*Quercus* spp.), dominates the lower parts of the mountain [73]. Such species distribution is mainly driven by the wide altitudinal range, namely by site-specific ecological conditions of different altitude levels. Generally, the climate in the Kopaonik NP is characterized as subalpine [70], with an average annual temperature of 4.1 °C and an average annual precipitation of 1040.1 mm (climatic sequence 1991–2020) [74]. By comparing the last two climatic sequences (1961–1990 and 1991–2020), it can be found that the average annual temperature in the Kopaonik NP increased by 1.4 °C, and the average annual precipitation increased by 119.3 mm [75]. As significant devitalization and dieback of trees are reported more frequently in pure stands and less in mixed stands of Norway spruce, we narrowed the research area down to 2385.72 ha of such forests, using forestry stand maps provided by the Kopaonik NP. A major component of the research area is located in the area under the protection regime of the second degree, where, according to Đorđević et al. [73], limited and strictly controlled use of natural resources and activities is established to the extent that it does not endanger natural habitats.

2.2. Data Collection

To evaluate the impact of drought on the forest cover loss at Mt. Kopaonik (Appendix A), we downloaded Landsat 7 (ETM+), Landsat 8 (OLI) Level 1, and Sentinel-2A/2B (MSI) Level 1C satellite imagery (from 2009 to 2022) using the U.S. Geological Survey Earth Explorer website (<https://earthexplorer.usgs.gov>, accessed 11 January 2024) and the Semi-Automatic Classification v.7.10.11-Matera (SCP) plugin [76] from the QGIS v.3.22.6 Białowieża (OSGeo, Chicago, IL, US) software (Tables 1 and 2). The 2009 to 2022 time period was selected to ensure that the state of vegetation in pre-drought (2009), drought (2011 and 2012), and post-drought (2013–2022) periods when severe pest outbreaks occurred was analyzed in order to obtain a complete picture of how Norway spruce is responding to the adverse effects of climate change. We selected only the cloud-free imagery acquired during the growing season, which, in our case, included imagery acquired only in July and August (except for one image from June). The 2010 imagery was not downloaded because, in all available Landsat 7 (ETM+) data, the images covering most of our research area were covered with clouds.

2.3. Data Processing

The downloaded Landsat 7 (ETM+) and Landsat 8 (OLI) MS bands, R, G, B, NIR, SWIR1, and SWIR2, including Sentinel-2 (MSI) Level-1C MS bands, B, G, R, VRE, VRE2, VRE3, NIR, NIR2, SWIR2, and SWIR3, were automatically processed using the SCP plugin by converting them from DN [Landsat] and scaled top of atmosphere (TOA) reflectance [Sentinel] into the TOA reflectance to reduce the inter-scene variability through a normalization for solar irradiance. Atmospheric correction of all images was carried out using an image-based technique called Dark Object Subtraction (DOS1) [77], as cited in [76]. Ordinary least squares regression (OLS) equations from Roy et al. [78] were used to normalize the reflectance of one Landsat sensor to the other (ETM+ to OLI). Before applying the pan-sharpening Brovey Transform technique [79] using the SCP plugin, as recommended by Rahaman et al. [80], we calculated individual relationships of Landsat 7 (ETM+) and Landsat 8 (OLI) R, G, B, and NIR bands with the PAN band using regression analysis with R Studio v.4.3.2 (Posit, PBC, Vienna, Austria) [81] and a raster [82] package. The

results showed weak relationships between those variables for several Landsat 7 (ETM+) MS bands, R: $r^2=0.44$, G: 0.62, and B: 0.41, except for NIR: $r^2=0.90$. Because of the possible distortion of spectral data that might occur after pan-sharpening these MS bands, which may produce misleading conclusions in time series analysis of vegetation indices (VIs), we only used original MS Landsat 7 (ETM+) bands. On the contrary, Landsat 8 (OLI) bands showed a strong relationship with the PAN bands R: $r^2=0.99$, G: 0.99, and B: 0.99, except for NIR: $r^2=0.54$. As such, we used pan-sharpened Landsat 8 (OLI) MS bands (R, G, and B) in forest cover loss analysis for the years 2013 and 2014.

2.4. Forest Cover Loss Analysis

The land cover classification was carried out using the Supervised (semi-automatic) classification, which involves identifying materials in the image according to their spectral signatures by drawing the Regions of Interest (ROIs—Training Areas) over the homogeneous area of an image. For the sake of precise drawing, we used high-resolution imagery of the year 2022, provided in Google Earth Pro v.7.3.6.9345-r0 (Google, Mountain View, CA, USA), overlaid with different MS band composites of downloaded imagery. Of all tested MS band composites, the so-called “agricultural composite” (SWIR1-NIR-B) and the “short-wave infrared composite” (SWIR2-SWIR-R) performed best in underling the difference between stands dominated by conifer or deciduous trees. In this way, we excluded stands dominated by deciduous trees from our analysis. Finally, we drew eleven reliable and constant ROIs for all years analyzed, six for forest cover (average area 6.17 ha) and five for non-forest cover (average area 7.24 ha), which were evenly distributed all over the area. Forest cover included all canopy undisturbed stands, while non-forest cover included forest glades, meadows, bare lands, and small artificial objects. After drawing all the ROIs, they were dissolved to form two land cover macro classes. Using the Land Cover Signature (LCS) classification in the SCP plugin [76], we defined spectral thresholds for each ROI signature (a minimum value and a maximum value of each MS band), defying the spectral region of each land cover macro class. Spectral thresholds were calculated for all years separately to avoid misclassification of land cover due to inter-year variability in the vegetation spectral characteristics. Pixels that were not classified in either of the two macro classes, that is, pixels found inside overlapping regions or outside any spectral region, were classified using the Minimum Distance algorithm [76,83]. In this way, Euclidean distance was calculated between the spectral signatures of every pixel in the image and ROI spectral signatures, thus assigning each pixel to the class of the spectral signature that was closest. After the land cover classification, the final raster processing was conducted using the Postprocessing group of tools in the SCP plugin, which included, to a certain extent, the correction of incorrectly classified pixels and the merging of rasterized polylines and polygons of roads and other artificial objects into classification rasters, whose incorrect classification may contribute to the misinterpretation of the results. Using the Accuracy function in the SCP plugin, the accuracy assessment of the produced maps (classification rasters) was performed with the calculation of an error (confusion) matrix by comparing produced map information with reference data [84], which was, in our case, high-resolution imagery provided in Google Earth Pro v.7.3.6.9345-r0 (Google, Mountain View, CA, USA) (CNES/Airbus, Maxar Technologies, etc.). Given that each produced map contained more than 100,000 pixels checking the classification accuracy of all of them would be impractical from several points of view. Therefore, a stratified random sampling method was used for this research. The total sample number was calculated for each analyzed year separately (from 2013 to 2022) by applying Equation (1) [85,86]:

$$n = \left(\frac{\sum W_i S_i}{S(\hat{O})} \right)^2 \quad (1)$$

where n is the number of samples (ROIs), $S(\hat{O})$ is the standard error of the estimated Overall Accuracy that we would like to achieve (here used as 0.01), W_i is the mapped proportion

of the area of map class, and S_i is the standard deviation of stratum (values proposed by Olofsson et al. [86]).

Sample size allocation to strata (map classes) of each analyzed year was calculated as an average number of proportional and equal sample size allocations previously calculated for each stratum. The random distribution of samples for each map class was conducted using the SCP tool Multiple ROI creation (to create stratified random points). The process of labeling (assigning) the sample units to each macro class was carried out using Google Earth Pro v.7.3.6.9345-r0 (Google, Mountain View, CA, USA) and upon its completion, the data were exported into KMZ format, which was finally converted into the shapefile (.shp) format to match SCP Accuracy tool requirements for the calculation of accuracy quantitative measures, such as Error Matrix, Overall Accuracy (OA), Producer's Accuracy (PA), and User's Accuracy (UA) [86]. Forest cover loss was calculated as the absolute and relative difference between the surface area of forest cover (ha) in the reference year (2013) and all other years consecutively. The cumulative forest cover loss dynamics were calculated on a fragment level, as an average area change of all of them, excluding non-forest areas existent in 2013. Land cover classification results visualization was conducted using R Studio v.4.3.2 (Posit, PBC, Vienna, Austria) [81] and a raster [82] package, and the sf [87], RColorBrewer [88], ggplot2 [89], ggpmisc [90], patchwork [91], and gt [92] packages.

2.5. Evaluation of VI Sensitivity in Detecting and Predicting Drought Effects in Norway Spruce Forests

To examine the state of forest health and vitality pre-drought and during the drought period (2009–2014) that preceded forest cover loss, we selected multiple VIs from different groups, such as Typical VIs, Water VIs, and wetness and greenness components of the Tasseled Cap (TC) transformation (Table 3).

The selection of VIs was based on their sensitivity in detecting various vegetation properties. For example, Typical VIs are well known for assessing photosynthetic activity, forest health status, and detecting forest stressors such as pest outbreaks [43,51,55,93–96]. On the other hand, Water VIs primarily provide a quantitative measure of water content in various tree species, early detection of water stress, and assessment of drought impacts on forested areas [48,51,52,57,96–99]. Tasseled Cap (TC) transformation components are selected as they compress multispectral data into a few bands associated with physical scene characteristics with minimal information loss [100], thus sharing or having greater sensitivity in detecting various vegetation properties of both Typical VIs and Water VIs [42,101,102].

Before the VI calculation, we averaged each MS band (TOA reflectance) on an annual basis, using R Studio v.4.3.2 (Posit, PBC, Vienna, Austria) [81], a raster [82] package, and sf [87] packages. Calculation of the VIs and their mean values, including VIs time series plot visualization, was conducted by using the R Studio v.4.3.2 (Posit, PBC, Vienna, Austria) [81], readxl [103], raster [82], sf [87], and RColorBrewer [88] packages.

A calculation of mean values was segregated on the spatial level to areas where forest cover loss occurred and to areas where it did not. The spatial distribution of those areas was taken from the land cover classification (LCC) rasters. For this purpose, we selected the years 2015 (when the bark beetle outbreak started) and 2017 (when the bark beetle outbreak reached its peak), excluding non-forest areas that were present in the LCC raster from the year 2014. By this means, data preparation was made for an analysis whose only purpose was to determine if there was an association between the spatial distribution of forest and forest cover loss and variation in VI values. Therefore, we used Cohen's d [108] to measure the effectiveness of the VIs in forest cover loss detection by determining whether or not there is a statistically significant difference between VI values in the areas of forest and non-forest cover (forest cover loss), and how large that difference is Equation (2). Calculation of Cohen's d was carried out using the R Studio v.4.3.2 (Posit, PBC, Vienna, Austria) [81] and lsr [109] packages. The effect size was classified using the Sawilowsky scale [110], where 0.1 represents a very small effect size, 0.2 a small effect size, 0.5 a medium effect size, 0.8 a large effect size, 1.2 a very large, and 2.0 a huge effect size. For this research, we only considered a medium, large, very large, and huge effect size sufficient to predict

forest cover loss. As such, according to Cohen's U3 [108], 69.1%, 79.8%, 88.5%, and 97.7%, respectively, of the lower-measured land cover class areas are exceeded by the average VI value in the higher-measured land cover class area:

$$d = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{SD_1^2 + SD_2^2}{2}}} \quad (2)$$

where \bar{X}_1 is the mean of the first group, \bar{X}_2 is the mean of the second group, SD_1^2 is the standard deviation of the first group, and SD_2^2 is the standard deviation of the second group.

To the following:

2.1. Study Area

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2.4. Forest Cover Loss Analysis

The land cover classification was carried out using the Supervised (semi-automatic) classification, which involves identifying materials in the image according to their spectral signatures by drawing the Regions of Interest (ROIs—Training Areas) over the homogeneous area of an image. For the sake of precise drawing, we used high-resolution imagery of the year 2022, provided in Google Earth Pro v.7.3.6.9345-r0 (Google, Mountain View, CA, USA), overlaid with different MS band composites of downloaded imagery. Of all tested MS band composites, the so-called “agricultural composite” (SWIR1-NIR-B) and the “short-wave infrared composite” (SWIR2-SWIR-R) performed best in underling the difference between stands dominated by conifer or deciduous trees. In this way, we excluded stands dominated by deciduous trees from our analysis. Finally, we drew eleven reliable and constant ROIs for all years analyzed, six for forest cover (average area 6.17 ha) and five for non-forest cover (average area 7.24 ha), which were evenly distributed all over the area. Forest cover included all canopy undisturbed stands, while non-forest cover included forest glades, meadows, bare lands, and small artificial objects. After drawing all the ROIs, they were dissolved to form two land cover macro classes. Using the Land Cover Signature (LCS) classification in the SCP plugin [80], we defined spectral thresholds for each ROI signature (a minimum value and a maximum value of each MS band), defying the spectral region of each land cover macro class. Spectral thresholds were calculated for all years separately to avoid misclassification of land cover due to inter-year variability in the vegetation spectral characteristics. Pixels that were not classified in either of the two macro classes, that is, pixels found inside overlapping regions or outside any spectral region, were classified using the Minimum Distance algorithm [80,87]. In this way, Euclidean distance was calculated between the spectral signatures of every pixel in the image and ROI spectral signatures, thus assigning each pixel to the class of the spectral signature that was closest. After the land cover classification, the final raster processing was conducted using the Postprocessing group of tools in the SCP plugin, which included, to a certain extent, the correction of incorrectly classified pixels and the merging of rasterized polylines and polygons of roads and other artificial objects into classification rasters, whose incorrect classification may contribute to the misinterpretation of the results. Using the Accuracy function in the SCP plugin, the accuracy assessment of the produced maps (classification

rasters) was performed with the calculation of an error (confusion) matrix by comparing produced map information with reference data [88], which was, in our case, high-resolution imagery provided in Google Earth Pro v.7.3.6.9345-r0 (Google, Mountain View, CA, USA) (CNES/ Airbus, Maxar Technologies, etc.). Given that each produced map contained more than 100,000 pixels checking the classification accuracy of all of them would be impractical from several points of view. Therefore, a stratified random sampling method was used for this research. The total sample number was calculated for each analyzed year separately (from 2013 to 2022) by applying Equation (1) [89,90]:

$$n = \left(\frac{\sum W_i S_i}{S(\hat{O})} \right)^2 \quad (1)$$

where n is the number of samples (ROIs), $S(\hat{O})$ is the standard error of the estimated Overall Accuracy that we would like to achieve (here used as 0.01), W_i is the mapped proportion of the area of map class, and S_i is the standard deviation of stratum (values proposed by Olofsson et al. [90]).

Sample size allocation to strata (map classes) of each analyzed year was calculated as an average number of proportional and equal sample size allocations previously calculated for each stratum. The random distribution of samples for each map class was conducted using the SCP tool Multiple ROI creation (to create stratified random points). The process of labeling (assigning) the sample units to each macro class was carried out using Google Earth Pro v.7.3.6.9345-r0 (Google, Mountain View, CA, USA) and upon its completion, the data were exported into KMZ format, which was finally converted into the shapefile (.shp) format to match SCP Accuracy tool requirements for the calculation of accuracy quantitative measures, such as Error Matrix, Overall Accuracy (OA), Producer's Accuracy (PA), and User's Accuracy (UA) [90]. Forest cover loss was calculated as the absolute and relative difference between the surface area of forest cover (ha) in the reference year (2013) and all other years consecutively. The cumulative forest cover loss dynamics were calculated on a fragment level, as an average area change of all of them, excluding non-forest areas existent in 2013. Land cover classification results visualization was conducted using R Studio v.4.3.2 (Posit, PBC, Vienna, Austria) [85] and a raster [86] package, and the sf [91], RColorBrewer [92], ggplot2 [93], ggpmisc [94], patchwork [95], and gt [96] packages.

2.5. Evaluation of VI Sensitivity in Detecting and Predicting Drought Effects in Norway Spruce Forests

To examine the state of forest health and vitality pre-drought and during the drought period (2009–2014) that preceded forest cover loss, we selected multiple VIs from different groups, such as Typical VIs, Water VIs, and wetness and greenness components of the Tasseled Cap (TC) transformation (Table 3).

The selection of VIs was based on their sensitivity in detecting various vegetation properties. For example, Typical VIs are well known for assessing photosynthetic activity, forest health status, and detecting forest stressors such as pest outbreaks [43,55,59,97–100]. On the other hand, Water VIs primarily provide a quantitative measure of water content in various tree species, early detection of water stress, and assessment of drought impacts on forested areas [48,55,56,61,100–103]. Tasseled Cap (TC) transformation components are selected as they compress multispectral data into a few bands associated with physical scene characteristics with minimal information loss [103], thus sharing or having greater sensitivity in detecting various vegetation properties of both Typical VIs and Water VIs [42,104,105].

Before the VI calculation, we averaged each MS band (TOA reflectance) on an annual basis, using R Studio v.4.3.2 (Posit, PBC, Vienna, Austria) [85], a raster [86] package, and sf [91] packages. Calculation of the VIs and their mean values, including VIs time series plot visualization, was conducted by using the R Studio v.4.3.2 (Posit, PBC, Vienna, Austria) [85], readxl [106], raster [86], sf [91], and RColorBrewer [92] packages.

A calculation of mean values was segregated on the spatial level to areas where forest cover loss occurred and to areas where it did not. The spatial distribution of those areas

was taken from the land cover classification (LCC) rasters. For this purpose, we selected the years 2015 (when the bark beetle outbreak started) and 2017 (when the bark beetle outbreak reached its peak), excluding non-forest areas that were present in the LCC raster from the year 2014. By this means, data preparation was made for an analysis whose only purpose was to determine if there was an association between the spatial distribution of forest and forest cover loss and variation in VI values. Therefore, we used Cohen's d [111] to measure the effectiveness of the VIs in forest cover loss detection by determining whether or not there is a statistically significant difference between VI values in the areas of forest and non-forest cover (forest cover loss), and how large that difference is Equation (2). Calculation of Cohen's d was carried out using the R Studio v.4.3.2 (Posit, PBC, Vienna, Austria) [85] and lsr [112] packages. The effect size was classified using the Sawilowsky scale [113], where 0.1 represents a very small effect size, 0.2 a small effect size, 0.5 a medium effect size, 0.8 a large effect size, 1.2 a very large, and 2.0 a huge effect size. For this research, we only considered a medium, large, very large, and huge effect size sufficient to predict forest cover loss. As such, according to Cohen's U_3 [111], 69.1%, 79.8%, 88.5%, and 97.7%, respectively, of the lower-measured land cover class areas are exceeded by the average VI value in the higher-measured land cover class area:

$$d = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{SD_1^2 + SD_2^2}{2}}} \quad (2)$$

where \bar{X}_1 is the mean of the first group, \bar{X}_2 is the mean of the second group, SD_1^2 is the standard deviation of the first group, and SD_2^2 is the standard deviation of the second group.

In Table 3, we would like to update the references in Column number 5. Thus, Table 3 will be updated from the following:

Table 3. The VIs used for the evaluation of drought effects on forest cover loss.

Category	Vegetation Indices	Abrev.	Formula	Reference
Water VIs	Moisture Stress index	MSI	$\frac{SWIR1}{NIR}$	[104]
	Normalized Difference Moisture Index	NDMI	$\frac{NIR - SWIR1}{NIR + SWIR1}$	[39]
	Disease Water Stress Index	DSWI	$\frac{NIR - GREEN}{SWIR1 + RED}$	[54]
	Normalised Multi-band Drought Index	NMDI	$\frac{NIR - (SWIR1 - SWIR2)}{NIR + (SWIR1 - SWIR2)}$	[51]
	Normalized Difference Vegetation Index	NDVI	$\frac{NIR - RED}{NIR + RED}$	[105]
Typical VIs	Enhanced Vegetation Index	EVI	$\frac{2.5 * (NIR - RED)}{NIR + 6 * RED - 7.5 * BLUE + 1}$	[106]
	Soil-Adjusted Vegetation Index	SAVI	$\frac{NIR - RED}{(NIR + RED + 1) * 1.5}$	[107]
	Transformed Vegetation Index	TVI	$\sqrt[2]{\left(\frac{NIR - RED}{(NIR + RED) + 0.5}\right)}$	[46]
TC components	Tasseled Cap Greenness (Landsat 8)	TCG	$BLUE * (-0.2941) + GREEN * (-0.243) + RED * (-0.5424) + NIR * 0.7276 + SWIR1 * 0.0713 + SWIR2 * (-0.1608) + BLUE * 0.1511 + GREEN * 0.1973 + RED * 0.3283 + NIR * 0.3407 + SWIR1 * (-0.7117) + SWIR2 * (-0.4559)$	[100]
	Tasseled Cap Wetness (Landsat 8)	TCW		[100]

To the following:

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	Normalised Multi-band Drought Index	NMDI	$\frac{NIR - (SWIR1 - SWIR2)}{NIR + (SWIR1 - SWIR2)}$	[55]
Typical VIs	Normalized Difference Vegetation Index	NDVI	$\frac{NIR - RED}{NIR + RED}$	[108]
	Enhanced Vegetation Index	EVI	$\frac{2.5 * (NIR - RED)}{NIR + 6 * RED - 7.5 * BLUE + 1}$	[109]
	Soil-Adjusted Vegetation Index	SAVI	$\frac{NIR - RED}{(NIR + RED + 1) * 1.5}$	[110]
	Transformed Vegetation Index	TVI	$\sqrt[2]{\left(\frac{NIR - RED}{(NIR + RED) + 0.5}\right)}$	[46]
TC components	Tasseled Cap Greenness (Landsat 8)	TCG	$BLUE * (-0.2941) + GREEN * (-0.243) + RED * (-0.5424) + NIR * 0.7276 + SWIR1 * 0.0713 + SWIR2 * (-0.1608) + BLUE * 0.1511 + GREEN * 0.1973 + RED * 0.3283 + NIR * 0.3407 + SWIR1 * (-0.7117) + SWIR2 * (-0.4559)$	[103]
	Tasseled Cap Wetness (Landsat 8)	TCW		[103]

In Section 4, Subsections 4.1–4.4, all the references were updated from the following:

4.1. Forest Cover Loss

In the example of the Kopaonik NP, it can be seen from the results of this study that Landsat 8 (OLI) and Sentinel 2A/2B (MSI) satellite imagery can be used, with satisfactory accuracy, in the mapping of small forest cover losses. Moreover, the high UA for non-forest cover (Table 5) also indicates satisfactory accuracy, as most pixels classified as non-forest cover represent the real state in the field. Nevertheless, both quantitative and qualitative accuracy assessments showed some minor drawbacks. For example, the lower PA for non-forest cover (Table 5) may indicate the impossibility of correctly classifying areas smaller than 10×10 or 15×15 m due to spatial resolution limitations of both sensors used (Sentinel 2 MSI up to 10 m and Landsat 8 OLI up to 15 m). Such was the case with KC et al.'s [111] land cover classification of Rupandehi District, Nepal, where barren land was classified as neighboring water bodies due to its small size. Sometimes, in an area of one pixel, we can find many different types of land cover, which significantly alter pixel spectral signature; thus, in the classification process, pixels can be assigned to the wrong land cover class. Inter-seasonal variation in vegetation photosynthetic activity and the current health status of forest cover may also alter its spectral signature, for example, to be similar to the neighboring non-forest cover (grassland or underbrush). This was observed by Forsythe et al. [56] to be the main reason for lower PA values in some classification results. The combination of both events surely contributed to the classification errors. Nevertheless, such errors can be ignored, as the undetected loss of several trees does not represent a significant error from the forestry management point of view.

Considering that 5.75% of the pure Norway spruce forest in the Kopaonik NP ceased to exist in the post-drought period (Figure 2), it is hard to attribute such a state exclusively to the drought effects. Kesić et al. [28] came to the same conclusion, claiming that soil acidification and monodominance of Norway spruce at Mt. Kopaonik were other possible reasons for its dieback. However, the nearly double increase in forest cover loss during 2015 and 2016 (Figure 2) can be easily attributed to the effects of pest outbreaks. As reported by Matović et al. [31] and Stojanović et al. [33], in those years, there was a huge outbreak of *I. typographus* and *P. chalcographus*, which, at that moment, acted like a primary pest. However, it should be taken into account that bark beetle outbreaks in Norway spruce forests are a consequence of adverse climatic effects, such as drought, as their defensive

mechanisms are weakened when affected by summer drought [112–115]. Spatial–temporal expansion of forest glades in 2015, 2016, and 2017, which previously emerged over small areas in 2014 (Figure 3 and Table 4), clearly indicate bark beetle activity. Such a trend continued in later years with less intensity, following a decline in bark beetle outbreaks. However, a few questions arise. Is the forest cover loss a result of a single factor or the interaction of several factors? Are particular stands more susceptible to drought than others? The answers to these questions should be sought through the implementation of various long-term multidisciplinary research projects in these forests.

4.2. Evaluation of VI Sensitivity in Detecting Responses to Drought and Predicting the Dieback of Norway Spruce

Although the NDVI, EVI, TVI, SAVI, TCG, DSWI, and TCW revealed a large-scale drop in vegetation vigor and canopy water content all over the analyzed area, that is, the response of Norway spruce to severe drought occurred in 2012 (Figure 4), not all VIs predicted forest cover loss in 2015 (Figure 5). Besides TCW, Cohen's d showed that other VIs, which did not show any response of Norway spruce to severe drought in 2012 (MSI, NDMI, and NMDI), had large and very large effects in predicting forest cover loss in 2015. A similar result was found for 2011, which was a year with less severe drought occurrence. Although the MSI [46] and NDMI [49] are considered to be highly effective in assessments of moisture stress in plants, this was not the case in our study. Based on such results, we can assume that NIR-SWIR1 ratio-based Water Vis, such as the MSI and NDMI, indicated only different soil water retaining capacities in areas where forest cover loss occurred and where it did not. We found the base for this assumption in a conclusion in Welikhe et al.'s research [104], where it was reported that MSI is strongly correlated to soil moisture at 20 cm depth. On the other hand, in a review study, Le et al. [49] summarized findings from other studies [98,116,117], concluding that the NDWI method (in our research named NMDI) yielded unsatisfactory results when applied to forest objects for water stress monitoring. Worth noticing is the large effect of the pre-drought (2009) results of the EVI, SAVI, TCG, and TCW in predicting the forest cover loss in 2015, as such a state points to pre-drought differences, and possibly the susceptibility of different Norway spruce populations, or their respective habitats, to drought events in the Kopaonik NP. The cause of this may be found in the research of Rehschuh et al. [118], in which they reported that Norway spruce trees growing on shallow, well-drained soil expressed a relatively higher drought sensitivity compared to trees from a site with deep, silty soil. The practically non-existent ability to predict the forest cover loss in 2015, with the post-drought data (2013 and 2014) using the NDVI and its modified version TVI, should not be considered unusual. Although these VIs showed strong sensitivity in the detection of Norway spruce response to severe drought, they cannot be used in predicting forest cover loss, as they do not exhibit any statistically significant difference between VI values in the area of forest and non-forest cover (forest cover loss). As such, we agree with Le et al.'s [49] conclusion stating that the NDVI cannot be effectively used in the early detection of drought effects. On the contrary, other “drought-sensitive” VIs, such as the EVI, SAVI, TCG, and TCW, showed a large (2013) to very large effect (2014) in predicting forest cover loss in 2015, indicating that the post-drought period is crucial in predicting drought effects, as it can strongly suggest where forest cover loss might occur. In contrast, these VIs, except for the TCW, did not perform well in predicting forest cover loss in 2017 (Figure 6), indicating that the primary cause of Norway spruce dieback after 2015 was mainly driven by pest outbreaks. As seen in Figure 2, forest cover loss doubled from 2015 to 2017. Such a finding goes in line with an earlier report from Matović et al. [31], where it was stated that, in those years, bark beetle began to act as a primary pest. What challenges this conclusion is a post-drought medium (2013) to a large effect (2014) of the DSWI and a large (2013) to a very large effect (2014) of the TCW in predicting forest cover loss in 2017 (Figure 6), which may indicate a direct influence of drought on the loss of forest cover in 2017. Nevertheless, so-called Water VIs (MSI, NDMI, and NMDI) performed almost the same as for 2015 forest cover loss prediction—having a

large (2012) to very large effect (2013 and 2014) in predicting forest cover loss. Considering these results together with previous conclusions, where we stated that such results only indicated different soil water retaining capacities in areas where forest cover loss occurred and where it did not, we can only confirm such assumptions.

4.3. Implication for Conservation of Norway Spruce Stands in the Kopaonik NP

As indicated by the results, severe drought greatly impacts forest cover loss in Norway spruce stands in the Kopaonik NP. Although severe drought has not occurred since 2012, according to Miletic et al. [37], such events may occur more often in the future. Accordingly, we can only expect that forest cover loss will continue to rise. However, we did not take into account several other reasons, which surely had or may have a great impact on forest cover loss. In their study in the Kopaonik NP, Matović et al. [31] found that devitalization and dieback of Norway spruce trees were more pronounced in structurally and age-homogeneous stands. As such, within areas of protective regimes, it should be legally enabled to implement adequate forest management measures that will support structural and age differentiation. Furthermore, the introduction of complementary species, such as Silver fir (*Abies alba* Mill.) and European beech (*Fagus sylvatica* L.), to improve stability and overall resistance of Norway spruce stands should not be neglected, as the monodominance of one species, such as Norway spruce, leads to instability and reduced tolerance to pests and adverse climatic events, as was proven in our and many other studies [119–121]. Regarding the deforested areas, support should be provided through tree planting. As Tanovski et al. [116] proposed, this should involve using reproductive material of known origin with adaptive properties suitable for the environmental conditions of the regeneration site.

4.4. Methodological Limitations of the Used Methodology in Detecting Responses to Drought and Predicting the Dieback of Norway Spruce

The main reason for some previously proven VIs, such as the NDWI, MSI, and NDMI [38,116], exhibiting low performance in monitoring and predicting the health status of Norway spruce forests in the Kopaonik NP may be the lower spatial or spectral resolution of the imagery used. Although, from 2015 until 2022, higher spatial and spectral resolution Sentinel 2 (MSI) imagery was used for land cover mapping, strong sensitivity in predicting forest cover loss using lower spatial and spectral resolution Landsat 7 (ETM+) and Landsat 8 (OLI) imagery was simply impossible due to various factors. For example, one pixel in Landsat 7 (ETM+) and Landsat 8 (OLI) imagery may have mixed spectral values, as it, in a spatial manner, contains up to three pixels from Sentinel 2 (MSI) imagery, which may include distinct land cover types. A similar problem was reported in Abdollahnejad et al.'s [42] study, which points out that lower-resolution satellite imagery has limited use; that is, it could be used only in studies where sample sizes are not less than the spatial resolution of used imagery. Taking into account that Sentinel 2 (MSI) has been in orbit since June 23, 2015, such shortcomings, in the context of this study, could not be overcome. Another problem lies in the low temporal resolution and unavailability of cloud-free Landsat 7 (ETM+) and Landsat 8 (OLI) imagery during the entire growing season in Kopaonik NP. If more were available, coupled with ground-measured meteorological data, it would be easier to determine which drought levels or their cumulative effects, along the growing season, trigger Norway spruce dieback in the future. On the other hand, the usage of very-high spatial and spectral resolution imagery, such as Pléiades 1A/1B, QuickBird, SPOT 6/7, WorldView-2, etc., could provide precise and clear answers even at the single tree level. However, their high cost was a limiting factor in the framework of this study. Considering that other factors, such as stand and terrain characteristics, play a significant role in Norway's spruce dieback [28,31,118], future analyses should include these factors. This can be achieved by employing machine learning methods to provide more accurate and reliable results.

To the following:

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In the example of the Kopaonik NP, it can be seen from the results of this study that Landsat 8 (OLI) and Sentinel 2A/2B (MSI) satellite imagery can be used, with satisfactory accuracy, in the mapping of small forest cover losses. Moreover, the high UA for non-forest cover (Table 5) also indicates satisfactory accuracy, as most pixels classified as non-forest cover represent the real state in the field. Nevertheless, both quantitative and qualitative accuracy assessments showed some minor drawbacks. For example, the lower PA for non-forest cover (Table 5) may indicate the impossibility of correctly classifying areas smaller than 10×10 or 15×15 m due to spatial resolution limitations of both sensors used (Sentinel 2 MSI up to 10 m and Landsat 8 OLI up to 15 m). Such was the case with KC et al.'s [114] land cover classification of Rupandehi District, Nepal, where barren land was classified as neighboring water bodies due to its small size. Sometimes, in an area of one pixel, we can find many different types of land cover, which significantly alter pixel spectral signature; thus, in the classification process, pixels can be assigned to the wrong land cover class. Inter-seasonal variation in vegetation photosynthetic activity and the current health status of forest cover may also alter its spectral signature, for example, to be similar to the neighboring non-forest cover (grassland or underbrush). This was observed by Forsythe et al. [60] to be the main reason for lower PA values in some classification results. The combination of both events surely contributed to the classification errors. Nevertheless, such errors can be ignored, as the undetected loss of several trees does not represent a significant error from the forestry management point of view.

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The list of updated and rearranged references is as follows:

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The authors apologize for any inconvenience caused and state that the scientific conclusions are unaffected. This correction was approved by the academic editor. The original publication has also been updated.

Reference

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