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Assessment of the State of Forests Based on Joint Statistical Processing of Sentinel-2B Remote Sensing Data and the Data from Network of Ground-Based ICP-Forests Sample Plots

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Abstract

The research was carried out on the territory of the Karelian Isthmus of the Leningrad Region using Sentinel-2B images and data from a network of ground sample plots. The ground sample plots are located in the studied territory mainly in a regular manner, laid and surveyed according to the ICP-Forests methodology with some additions. The total area of the sample plots is a small part of the entire study area. One of the objectives of the study was to determine the possibility of using the k-NN (nearest neighbor method) to assess the state of forests throughout the whole studied territory by joint statistical processing of data from ground sample plots and Sentinel-2B imagery. The data of the ground-based sample plots were divided into 2 equal parts, one for the application of the k-NN method, the second for checking the results of the method application. The systematic error in determining the mean damage class of the tree stands on sample plots by the k-NN method turned out to be zero, the random error is equal to one point. These results offer a possibility to determine the state of the forest in the entire study area. The second objective of the study was to examine the possibility of using the short-wave vegetation index (SWVI) to assess the state of forests. As a result, a close statistically reliable dependence of the average score of the state of plantations and the value of the SWVI index was established, which makes it possible to use the established relationship to determine the state of forests throughout the studied territory. The joint use and statistical processing of remotely sensed data and ground-based test areas by the two studied methods make it possible to assess the state of forests throughout the large studied area within the image. The results obtained can be used to monitor the state of forests in large areas and design appropriate forestry protective measures.

Keywords

Remote Sensing, Sentinel-2B Imagery, ICP-Forest Sample Plot, Tree Stand, Damage Class, k-NN (Nearest Neighbor Method), Vegetation Index SWVI, Nonlinear Regression, Systematic Error, Random Error

1. Introduction

The state of forests has always been of great importance from the point of view of ecology, nature conservation, forestry and forestry industry due to their unique economic, environmental and social functions. In recent years, according to the ICP-Forests monitoring system [1], there has been a deterioration in the state of forests in Europe, for example, almost a third of the test areas of the system are moderately or severely damaged, and the dynamics over time of mean defoliation of tree crowns shows its increase, on the one hand, and a decrease in the number of completely healthy trees, on the other.

The main damaging forest factors are forest fires, insect attacks, pests and diseases, unfavorable weather conditions and different kinds of anthropogenic influences. It is shown that in Europe visible signs of tree damage were presented on almost half of the trees monitored in 2019. The most frequently reported biotic factors causing damage to trees were insects and drought became the main abiotic factor.

In Russia, forest fires are the main factor damaging forests, the areas of forests that they damage have increased substantially in recent years and amount to many millions of hectares [2].

Thus, it is confirmed that forest damage occurs over vast areas of millions of hectares. To counteract this, it is necessary to organize continuous monitoring of forests. The condition of forests is assessed as a result of their survey on networks of test areas, for example, according to the ICP-Forests program or by special expeditionary research. In both cases, the share of the surveyed area is a small part of the entire controlled territory, which makes it necessary to transfer information from the surveyed test areas or routes to the entire territory. Such a task must be solved with the help of remotely sensed data of the Earth, data from ground test areas and routes, as well as special statistical methods for processing combined information from these two sources.

The close to border forests health status is of large issue of both countries Russian Federation and Finland first due to the fact of possible chances for cross-border transport of pollutants, forest fires, pests and diseases. This territory is relatively dense populated. There is a well-developed road network from the both sides of the border. This area intensively used for different kinds of economic and social activities. Some of them such as forestry, recreation, tourism, sport, hunting, fishing, ecological farming, schooling and training are sensitive to forest health status. That is why authorities at regional and municipal levels, including forest authorities and nongovernmental groups of interests representing local people, are interested in the information on study area forests status. It is practical to use for the tree stands health status estimations on study area the level 1 regular grid of PSP established according ICP-Forests methodologies. At least two motives may also be referred to in want of such a decision: first, ICP-Forests program used to be applied for a long time in both countries, so about the identical grids of sample plots are already existed in each country, second, the methodology of field assessment of sample plots is exactly the identical and the results of all estimations and assessments will be comparable, which is very essential for between countries comparisons and conclusions.

The main objectives of this study were to test the utility of the k-NN method to assess the state of forests throughout the whole studied territory by joint statistical processing of data from ground sample plots and Sentinel-2B imagery, as well as examine the possibility of using the short-wave vegetation index (SWVI) calibrated on ground-based data to assess the state of forests of study area. In the course of the study, the idea of mandatory joint use of Earth remote sensing materials and ground-based sample areas was considered. To obtain reliable characteristics of the state of forests, it is necessary to calibrate and verify remotely sensed data based on field sample plots. Otherwise, the picture of the state of forests may be distorted.

2. Background

The k-NN method of remotely sensed data classification occupies a special place among other methods for researchers in the field of forest management and forest monitoring. This method makes it possible to combine in one procedure the use of Earth remotely sensed data and data obtained from ground-based polygons. This possibility may be of interest for assessing the state of forests. The k-NN method for studying forests was first proposed and then put into practice by Finnish researchers [3] [4] [5] [6]. In the early 2000s, many studies were published aimed at a comprehensive analysis of the possibilities and limitations of the k-NN method [7]-[12].

Part of the publications related to k-NN is devoted to the results of the experimental use of the method to solve the problems of the national forest inventory (NFI) in individual countries that differ in natural and economic conditions, forest management features, as well as tasks solved within the framework of the NFI [13] [14] [15]. Experiments on the use of the k-NN method were carried out in the NFI system of Sweden, USA, Norway, China, Germany and some other countries [16].

In recent decades, the study of the use of various vegetation indices for classifying and assessing the characteristics and health of vegetation, soils, and crops has become one of the most popular areas of remote methods. Additional reasons for the development of this direction are substantial technical progress associated with an increase in the number of satellites, improvement in the characteristics of remotely sensed materials, increasing their availability for numerous users, and continuous improvement of software and processing algorithms.

The basic foundations of the definition and interpretation of vegetation indices are set out in a number of textbooks and monographs [17]-[23]. Remotely sensed data processing programs, geoinformation systems and special applications can serve as tools for determining and studying vegetation indices based on remotely sensed materials [24] [25].

Brief overviews of spectral characteristics of vegetation as properly as 27 vegetation indices which might also be determined by software ENVI are performed in [26]. It is mentioned that the predominant advantage of vegetation indices is the ease of obtaining them and a broad vary of tasks solved with their help. It is also noted that for particular natural conditions and number tasks, some indexes can provide more accurate predictions than others. The determination of an index that displays the investigated property as precisely as possible is carried out via comparing the results of index calculations with field data. It is additionally noted that any vegetation indices provide only relative estimates of the properties of vegetation cover, which can be interpreted and recalculated into absolute ones with the involvement of field data. The index values are influenced by using the characteristics of the sensor and shooting conditions [18] [27].

A large number of studies are devoted to solving the problems of identifying and analyzing the relationship between vegetation indices and forest characteristics, as well as developing and improving forest monitoring methodology based on satellite data [28]-[33].

3. Materials and Methods

The studies became carried out on the territory of the Vyborg district of the Leningrad region. The trial regions are organized as a regular network with a step of 4 - 8 km. Every trial area was implemented as permanent sample plot (PSP) and is a 4-element cluster North-South and West-East orientated, including 4 subplots on each of which became evaluated the state of 6 specially selected sample trees. The methodology of undertaking field work is defined in detail in [34] and effectively was extensively used in some of different special researches [35] [36] [37] [38].

A total of 99 sample plots were surveyed, during the field work and then included in the database for further processing. In **Table 1** data on the predominant tree species in the surveyed sample areas are given. Six species of woody plant became tested on PSP: Scots pine (Pinus sylvestris), Norway spruce (Picea abies), Birch (Betula pendula), Aspen (Populus tremula), Black alder (Alnus glutinosa) and Gray alder (Alnus incana). Four of them Scots pine, Norway spruce, Birch and Aspen occupied a dominant position on PSP even as two species Black and Grey alder have been presented through single trees.

Table 1. Dominating tree species on sample plots located in Vyborg district of Leningrad region.

Tree species	Number of sample plots	Percent, %
Scots pine	59	59.6
Norway spruce	28	28.3
Birch	11	11.1
Aspen	1	1.0
Total	99	100.0

From the data in **Table 1** and **Figure 1**, it can be seen that Scots pine and Norway spruce predominate on the territory—they occupy 87.9% of the total number of sample plots. The health status of 2416 trees was assessed using the ICP-Forests methodology based on estimates of defoliation and discoloration of trees crowns assessments during field work. As a result, every sample tree become attributed via health status grade: 0—complete health tree, 1—slightly damaged, 2—moderately damaged, 3—severely damaged and 4—dead tree. Species distribution of the trees is provided in **Table 2**.

Table 2 data demonstrate that in the total number of model trees evaluated in the study area in the Vyborgsky district of the Leningrad region, Scots pine and Norway spruce predominate.

The developed method of field observations at each PSP included the registration in a circle with a radius of 100 m from the central tree of a set of additional characteristics related to the tree stand health and vitality: occurrence of infrastructural elements, garbage dumps, footprints of cuttings, thinning, forest fires, wind withdrawals, snow and frost damage to trees, recreation footprints (fire places, campfire, walking trail) and other signs of forest damage. With the help of maps and satellite data, the proximity of the PSP to quarries and settlements was determined.

To characterize the forest health status, mean damage class was calculated for each sample plots (see **Table 3**). This variable is considered as a quantitative measure of forest health status at tree stands level and as initial data for spatial analysis in geographic information systems (GIS).

To be able to interpret **Table 3** data statistics the subsequent scale was used: full healthy tree stands were those with a mean damage class in the range of 0 - 0.5, slightly damaged 0.51 - 1.50, moderately 1.51 - 2.50, severely damaged 2.51 - 3.50, dying and dead 3.51 - 4.00. **Table 3** information says that stands of all tree species are either healthy (spruce, birch) or slightly damaged (pine), broadleaves are in better condition than coniferous ones, and pine stands are most damaged. In general, the state of stands in the border region of Russian Federation and Finland on the part of Russia, within the Vyborg district of the Leningrad region, may be assessed as good: 56 sample plots were assessed as completely healthy and 43 as slightly damaged. To increase the statistical representation of the tree stands with negative health status, forest allotments with severe

Table 2. Species distribution of the trees estimated on the grid of sample plots.

Tree species	Number of trees	Percent, %
Scots pine	1329	55.0
Norway spruce	668	27.6
Birch	383	15.9
Aspen	31	1.3
Alder gray	3	0.1
Alder black	2	0.1
Total	2416	100

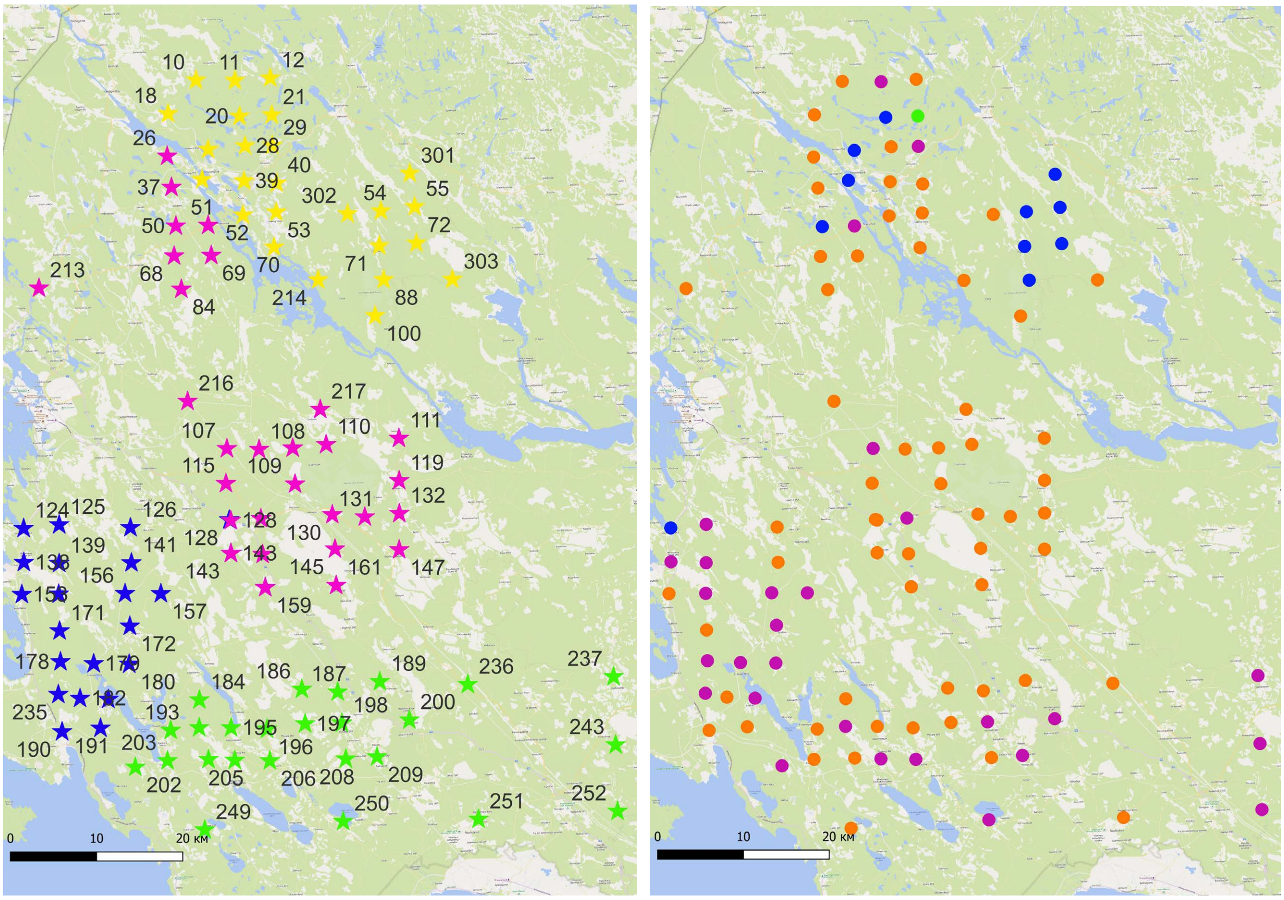
Table 3. Mean damage class of the main forest species and groups of species on the surveyed sample areas.

Tree species or group of species	Mean damage class
Scots pine	0.69
Norway spruce	0.40
Coniferous	0.59
Birch	0.28
Broadleaves	0.28
All species	0.54

damaged, dying and dead tree stands were added to the ground based data. To solve this problem, forest management data from standard geoinformation databases of the North-Western forestry enterprise were used. With the help of WinGIS and PLP-2015 programs, a set of forest parcels was selected from databases, for which the degree of damage was marked as severely damaged, drying out, as well as dead stands. Then, a set of polygons with the boundaries of forest parcels with severely damaged, drying and dead stands was exported from the forest management databases to the GIS. The suitability of selected plots for further analysis was assessed using fine spatial resolution images from the public domain (Bing, Google and Yandex). In total, 153 ground sample areas were used during processing, which were divided into two equal groups. Training trial plots were used to classify the territory according to the degree of vegetation damage, and control plots were used to assess the quality of the classification.

3.1. k-NN Classification Method

A general description of the kNN method is as follows [7]. The spectral distance, $d_{pi,p}$ is computed in the feature space from the pixel p to be classified to each pixel p_i for which the ground measurement or class is known. For each pixel p, take k-nearest field plot pixels (in the feature space) and denote the distances from the pixel p to the nearest field plot pixels by $d_{pi,p},\cdots,d_{pk,p}$ ($d_{pi,p} \le \cdots \le d_{pk,p}$). The estimate of the variable value for the pixel p is then expressed as a function



(a) (b)

Figure 1. Distribution of sample plots over study area (a) and dominating species on sample plots (Scots pine—orange, Norway spruce—violet, Birch—blue, Aspen—green) (b). Scale 1:350000.

of the closest units. In case of numerical variable all of the nearest neighbor values are taken in consideration, but each of them has weighed proportionally to the distance from classifiable pixel. A commonly used function for weighting distances is:

$$w_{(pi)p} = \frac{1}{d^t_{(pi)p}} \Bigg/ \sum_{j=1}^{k} \frac{1}{d^t_{(pi)p}}, \tag{1}$$

where: $w_{(pi)p}$ —vector of weighting values, $d^t_{(pi)p}$ —feature space distance from classifiable (p) and sample data (p_i), $t = 2$.

The estimate of the variable m for pixel p is then:

$$\hat{m}_p = \sum_{i=1}^{k} w_{pi,p} m_{pi}, \tag{2}$$

where:

$\hat{m}_p$ —numerical value of the parameter to be classified for the classifiable pixel;

m_{pi} —value of the parameter to be classified for nearest neighbor pixel p_i.

Classification of the Sentinel image by the k-NN method according to the damage classes of tree stands was performed on the basis of the training part of the sample plots. To determine the quality of the classification, the results of the classification were compared with the data of the control sample areas. The following formulas were used to calculate systematic and random (standard deviation) errors:

$$\Delta x = \frac{\sum_{i=1}^{n}\left(x_r^i - x_g^i\right)}{n}, \tag{3}$$

here Δx is a systematic error in determining the damage class of tree stands, points; x_r^i and x_g^i are the damage classes of tree stands obtained as a result of Sentinel image classification by the k-NN method and ground-based methods, respectively; n is the number of control sample plots.

$$\mathrm{SD} = \frac{\sqrt{\sum_{i=1}^{n}\left(\Delta x_i - \Delta x\right)^2}}{n-1}, \tag{4}$$

here, SD is a random error in determining the state class of stands, points;

$\Delta x_i = x_r^i - x_g^i$ is an error in determining the tree stand damage class by ground and remote methods for the control test sample plot i, points.

The Sentinel-2B satellite image (date of shooting July 31, 2018) was used to classify the state of the forest. A single multi-spectral image was formed from 4 spectral channels with a spatial resolution of 10 m: 8—NIR, 4—Red, 3—Green, 2—Blue. On **Figure 2** is shown the location of the ground sample plots in the study area.

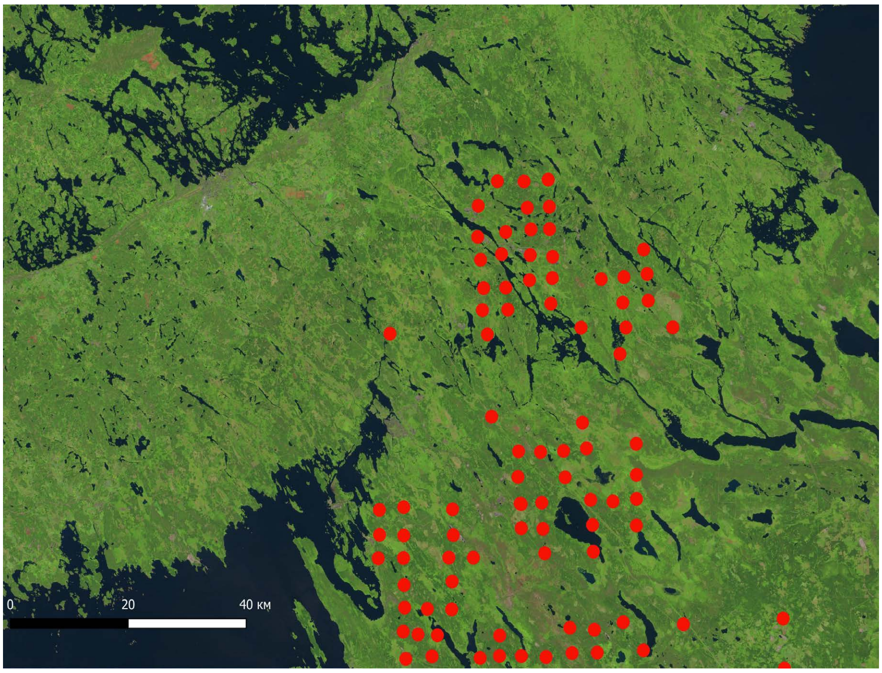


Figure 2. Sentinel—2B image combined with a map with location of the ground sample plot network. Scale 1:500000.

Pre-processing of survey materials (atmospheric correction, multi-spectral image formation) was performed using GIS QGIS 3.10.11-A Coruna and the Semi-Automatic classification plugin [39]. To perform classification by the k-NN method was carried out using the QGIS Desktop 2.14.12 GIS with the k-NN classifier plugin [40]. The initial settings of the k-NN classifier plugin used for classification were: the number of nearest neighbor $k = 5$, the number of spectral channels—four, and the classification mode—for continuous values.

3.2. Short-Wave Vegetation Index SWVI

In the process of the study, a set of known vegetation indices [26] was considered to assess the state of forest stands based on the Sentinel image. But substantial statistical dependencies between the values of the index and the damage classes of forest stands were obtained only for the short-wave vegetation index SWVI. The short-wave vegetation index SWVI is calculated from the NIR and SWIR bands:

$$\text{SWVI} = \frac{\text{NIR} - \text{SWIR}}{\text{NIR} + \text{SWIR}}, \tag{5}$$

here, NIR is the reflection of vegetation cover in the near-infrared part of the spectrum with a range of 0.76 - 0.9 microns; SWIR is the reflection of vegetation cover in the mid-infrared part of the spectrum with a range of 1.55 - 1.75 microns.

The Statgraphics 18-X64 software was used to find and study the relationship between the value of the short-wave vegetation index SWVI and the damage classes of tree stands. The possibilities of variance and regression analysis were used.

4. Results and Discussion

4.1. k-NN Classification Method

After classification of the Sentinel-2B image by k-NN method made on the base of training PSP calculations of systematic and random errors were done for testing PSP to estimate the classification quality. On **Figure 3** is shown one of the results of the k-NN classification—a thematic map, coloured by tree stand damage classes.

After calculating the errors, the following values were obtained: the systematic error was equal to zero ($\Delta x = 0$ points), and the random error was 1 point (SD = 1 point). These error values mean that there is no systematic error in the resulting classification, and as a result of a random error, the health status of forest stands can be mistakenly determined by 1 point better or worse compared to the actual value. Taking into account that the obtained error values can be assessed as not very substantial, and the use of the k-NN method can be considered suitable for classifying forest stands by damage classes.

increase the reliability of the results. This method can be used to solve many The proposed method for classifying the health state of forests is based on the joint use of remote sensing data and field sample plots, which can substantially

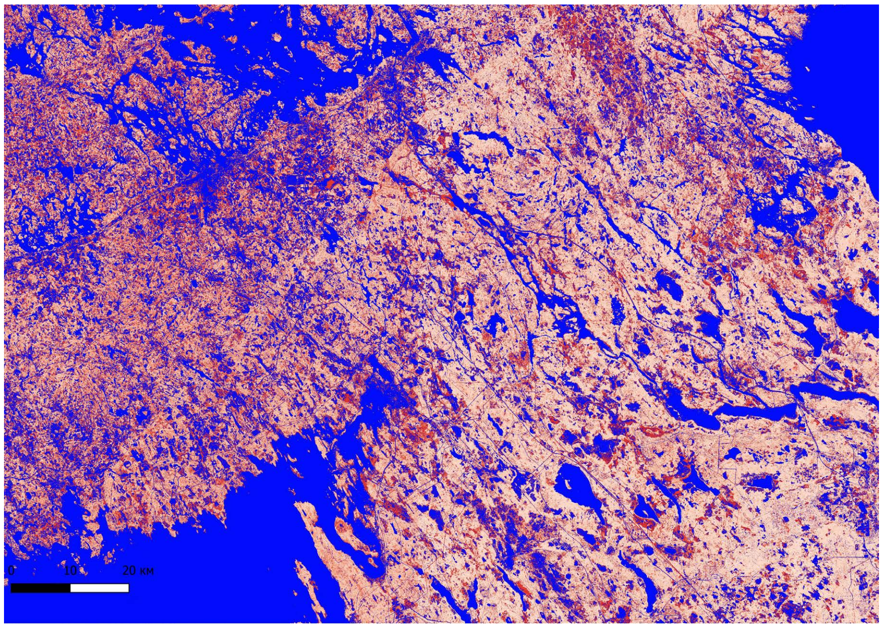


Figure 3. Thematic map of the study area coloured according damage class of forest tree stands. Scale 1:500000.

pressing problems of modern sustainable forest management, such as:

- planning activities for the use, reproduction, protection and conservation of forests based on their condition;
- identification and mapping of forests according to the degree of damage;
- development of strategies for forest management planning for damaged forests, taking into account preserving their stability and sustainability;
- identification and study of the causes of forest damage and planning of measures to mitigate and eliminate them.

4.2. Short-Wave Vegetation Index SWVI

The results of the analysis of variance showed a significant relationship between the damage classes of forest stands and the vegetation index SWVI (see Table 4).

The F-ratio (Fisher criteria), reflecting the level a ratio of the between-group estimate to the within-group estimate is 44.53. Since the P-value of the F-test is less than 0.05, there is a statistically significant difference between the mean vegetation indexes SWVI from one level of damage class to another at the 95% significance level. Based on the fact that the P-value of the F-test is less than 0.05, it can be argued that there is a statistically significant difference in the mean values of the SWVI vegetation indices between damage classes at a 95% significance level. Graphical analysis of the average values of damage classes shows a significant (more than 4 times) difference between the average index value from 0.08 for dead stands to 0.34 for healthy stands, which indicates the sensitivity of the SWVI index to the state of forest stands. But the graph also shows that the values of the SWVI index for some classes practically do not differ from each other. For

Table 4. ANOVA table for vegetation index SWVI by 5 damage classes.

Variability source	Sum of Squares	Degree of freedom	Mean square	F-ratio	P-value
Between damage classes	1.63300	4	0.408251	44.53	0.000
Within damage classes	1.35677	148	0.009167		
Total	2.98977	152			

example, healthy and slightly damaged stands (see **Figure 4**).

The relationship between mean trees stands damage classes and vegetation index SWVI may be approximate by invert logistic curve:

$$\text{Mean damage class} = 4 \big/ \left(1 + a * \exp\left(-b * \text{SWVI}\right)\right)$$

where a and b are curve parameters. The shape of the curve statistically reliable describing the relationship between vegetation index SWVI and tree stands mean damage classes is shown on **Figure 5** and illustrated the uncertainty in determining neighboring damage classes by the value of index.

The large coefficient of determination of the curve equal to 83.5% once again confirms the close relationship between the vegetation index SWVI and the average class of damage to stands on PSP.

In order to increase the resolution of damage class determination it was decided to build new aggregated classes: the first aggregated class included healthy and slightly damaged stands, the second—moderately damaged and severely damaged stands, and the third—dead stands. The results of the analysis of variance for the aggregated classes of the vegetation index SWVI are presented in **Table 5** and **Figure 6**.

The results of the analysis of variance for the aggregated classes demonstrated a significant increase in the statistical relationship between the SWVI index and the aggregated damage classes. According to the performed analysis of variance for vegetation index SWVI by 3 aggregated damage classes, the F-ratio (Fisher criteria) equals 82.56, that almost twice more than in **Table 4** (44.53). **Figure 6** shows that the 95% confidence intervals for mean values of index SWVI calculated for 3 aggregated damage classes haven't interceptions and can be used for damage class determination on higher stage of confidence.

The relationship for damage class calculation using the vegetation index SWVI as an explaining variable in this case of aggregated classes is linear with large coefficient of determination:

$$\hat{I}_A = 3.753 - 8.453 * \text{SWVI}, \quad R^2 = 89.4\%,$$

where I_A—aggregated damage class. The resulting equation can be used to calculate the health state of forests and develop thematic maps based on remotely sensed data.

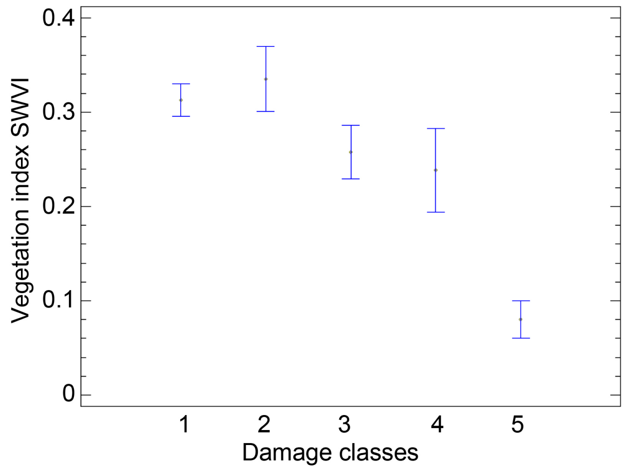


Figure 4. Mean values of vegetation index SWVI and 95% confidence intervals for tree stands 5 damage classes.

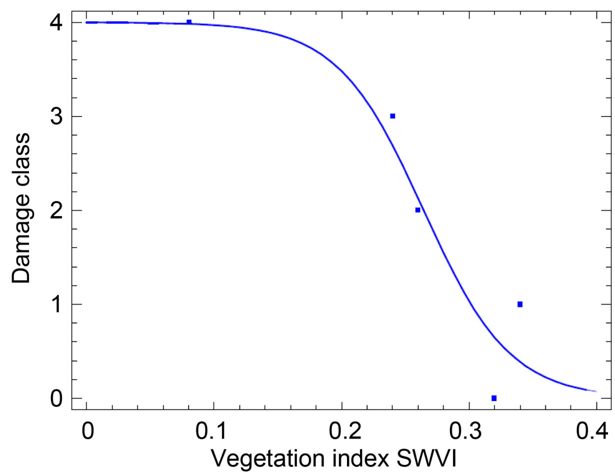


Figure 5. Relationship between vegetation index SWVI and tree stands mean damage classes (R^2 = 83.5%).

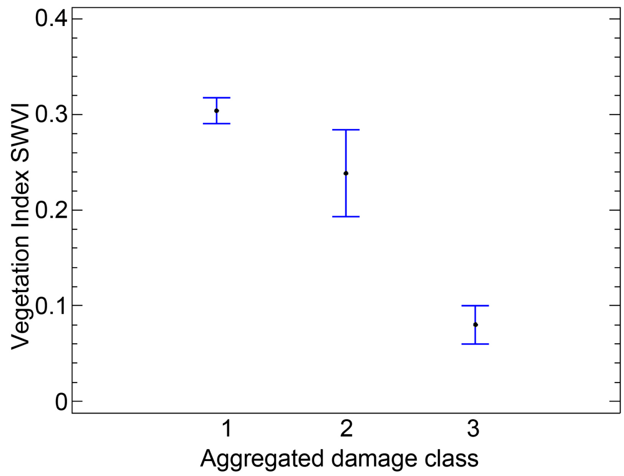


Figure 6. Mean values and 95% confidence intervals of vegetation index SWVI for tree stands aggregated damage classes.

Table 5. ANOVA table for vegetation index SWVI by 3 aggregated damage classes.

Variability source	Sum of Squares	Degree of freedom	Mean square	F-ratio	P-value
Between damage classes	1.56663	4	0.7833	82.56	0.000
Within damage classes	1.42314	148	0.0095		
Total	2.98977	152			

5. Conclusion

The k-NN approach of forest classification based totally on the joint use of remotely sensed data and ground-based sample areas has been broadly used in many countries for national forest inventories, mainly in Finland. With its help, objective data for large areas have been acquired during the forest inventory and the method demonstrated its practical effectiveness. In this study the k-NN approach was used to predict the condition and extent of damage to tree stands, which are also of great significance for solving some specific problems of sustainable forest management. The results of the application of developed methodology to assess the state of forests over large areas based on the k-NN approach were positive. A very important result is that the approach does not give systematic errors, and a random error creates uncertainty only when determining neighboring classes of damage to tree stands, which is not critical for its application. This method makes it possible to extrapolate data on the health status of tree stands on PSP, which in the geographical sense are points, to the entire territory represented through the satellite image. Applicability of the k-NN approach for estimation of forest health in assembles with ICP-Forest ground PSP is of significance due to the fact this network covers all the Europe and similar monitoring grids exist in the number of countries.

Some other end results of this study consist in revealed high sensitivity of short-wave vegetation index SWVI on tree stand health state as reflected by using its mean damage class. The value of SWVI varies as much as 4 times for healthy and dead tree stands. The higher the index value, the better the health status of plantings. If in analysis use the 3 aggregated damage classes instead of 5 preliminaries usually used the resolution ability of vegetation index SWVI elevates as much as twice and relationship between index value and aggregated damage classes became linear with large determination coefficient. This feature may be successively used for thematic mapping by means of GIS technology for visualization and evaluation of forest health state at the regions of interest. The practical application of this approach may be related to monitoring the condition of forests in remote areas. Thematic maps that replicate the state of plantings may be interesting to various fascinated organizations and agencies of citizens, such as state forestry management bodies, environmental organizations, hunters, fishermen and different recreational workers.

Generally, the methods primarily based on k-NN classification and use of vegetation index SWVI can be recommended for solving many issues of forestry related to monitoring the state of forests. Mainly, it could be used to organize nonstop monitoring of the health status of forests on the basis of acquiring updated materials of remote sensing for constantly informing involved companies of the population about the consequences.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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