

## Methodology for determining deforestation areas in Lviv region using remote sensing data

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**Abstract:** The object of the study is the processing of space images on the territory of the Carpathian territory in the Lviv region, obtained from the Landsat-8 satellite. The work aims to determine the area of deforestation in the Carpathian territory of the Lviv region from different time-space images obtained from the Landsat-8 satellite. Methods of cartography, photogrammetry, aerospace remote sensing of the Earth and GIS technology were used in the experimental research. The work was performed in Erdas Imagine software using the unsupervised image classification module and the DeltaCue difference detection module. The results of the work are classified as three images of Landsat-8 on the territory of the Carpathian territory in the Lviv region. The areas of forest cover for each of them for the period of 2016-2018 have been determined. During the three years, the area of forests has decreased by 14 hectares. Our proposed workflow includes six stages: analysis of input data, band composition of space images on the research territory, implementation of unsupervised classification in Erdas Imagine software and selection of forest class and determination of implementing this workflow, the vector layers of the forest cover of the Carpathians in the Lviv region for 2016, 2017, 2018 were obtained, and on their basis, the corresponding areas were calculated and compared.

**Keywords:** Landsat-8, remote sensing, space images, satellite monitoring system, logged area



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## 1. Introduction

The ecological state of the territory determines both the general concept of economical use of the territory and many private issues (development or reduction of certain industries, comfort of living, features of recreational use of the territory, etc.) (Burshtynska et al., 2014). Integrated ecological and digital maps are effective means of visual and generalized representation of the ecological situation within a specific territory (Burshtynska et al., 2015). Various information sources, such as aerospace images, are used in the mapping.

Forests cover over 15.7% of the territory of Ukraine (9.58 million hectares) and are located mainly in the north (Polissya) and west (Carpathians). They are important socioeconomically and ecologically, provide valuable resources, ensure the conservation of a significant portion of the world's carbon stock, serve as an ecological framework for the conservation of ecosystem biodiversity, and perform a variety of other biosphere functions. Ukraine's forestry is governed by the Forest Code, which was adopted in 1994 and has since been amended, as well as other normative legal documents. The Cabinet of Ministers of Ukraine approved the State Target Program "Forests of Ukraine" for 2010–2015 in September 2009. The program aimed to identify the main directions for sustainable forestry development aimed at strengthening the ecological, social, and economic functions of forests.

The need to conduct regular monitoring of forests is stipulated by their continuous dynamics as a result of natural and anthropogenic factors (fires, deforestation, man-made pollution, etc.). The scale of this impact varies significantly by region.

The Earth remote sensing data and the results of their thematic processing are now gaining increasing practical use in implementing control and supervision functions by various environmental organizations (Beaumonta et al., 2005; Zhe et al., 2012; DeVries et al., 2015; Hermosilla et al., 2016). Space images with an average spatial resolution from the satellite Landsat-8 are the most common for thematic remote sensing activities. The widespread use of space images from this device is based on information availability and a high (from 16 days) frequency of repetitive information (Clerici et al., 2012; Dorozhynskyy et al., 2013; Vershigora and Husak, 2013; Lewis et al., 2015; Hamunyela et al., 2016, Hnatushenko et al., 2016).

The task of forest monitoring to determine the strategy of rational forest use and environmental protection necessitates the widespread use of remote sensing technologies (both space and aviation), satellite navigation systems, and GIS technologies for collecting, processing, and analyzing information on forest resources in conjunction with data from aero visual inspections and traditional ground methods of forest pathological researches. This comprehensive approach allows collecting a large array of relevant data and to create reliable maps characterizing the state of forests, use the results in the processes of state forest cadastre, comprehensive accounting and evaluation of natural resources, forest management, protected areas administration, etc.

According to the territorial coverage, there are the following monitoring levels: global (continent, part of the world), national (country), regional (region), local (district, village, town, or city council), local (insignificant in area object, allocated according

to environmental, landscape or other criteria (park, tract, part of forest)). Following the methods of observation, forest monitoring is divided into geo-information monitoring (creation of electronic maps) and cartographic monitoring (creation of traditional maps, plans, outlines and schemes). According to the purpose, there are following types of monitoring: general (standard) – is carried out according to a set of basic indicators for the entire territory; scientific (background) – is based on a number of different indicators for research (mainly in reserves); special (operational-crisis) – on a certain set of indicators for a specific or entire territory (for example, to assess the fire risk, the state of development of certain emergencies, and the possibility of their localization and elimination).

There are three types of observations: remote, geodetic, and combined monitoring. There are three types of monitoring based on the frequency of observations: continuous (during fire season, in potentially dangerous areas), systematic (performed according to a specific plan and set of rules), and periodic (determination of snow cover, phenological condition of forests).

The list of problems to be solved during forest monitoring varies by area. Mainly it includes the updating of forest inventory data, protection of forests from fires, and partial control over the condition of forests, the order of forest use and implementing reforestation. Considering the existing practice and functions of forestry, forest industry, ecological and environmental organizations, a list of problems that should be solved within the framework of complex forest monitoring has been developed.

The functional problems of forest monitoring can be divided into eight groups:

- 1) protection of forests from fires;
- 2) control over the sanitary and pathological condition of forests;
- 3) observations of areas contaminated with radionuclides;
- 4) monitoring the order of forest use and reforestation;
- 5) observation of the condition and dynamics of forests, woody and shrubby vegetation on lands that are not part of the forest fund;
- 6) monitoring the condition and dynamics of woody and shrubby vegetation on agricultural lands that are not part of the forest fund;
- 7) assessment of the state of forest ecosystems and forest cover;
- 8) update data about the study of forests.

The list of problems is not final. When creating a united complex monitoring system, this list may be clarified and supplemented. Since forest monitoring works effectively only in the presence of reliable data on forests and developed GIS, the eighth task can be considered as a priority. The complex multipurpose GIS of different levels (national, regional, local) should be formed and maintained in an updated state considering the information about forests. The solution to these problems is possible only under the condition of a combination of all types of observations and measurements, the main of which are remote (aerospace).

The primary stages of forest monitoring using aerospace information are:

- acquisition and pre-processing of aerospace information;
- acquisition and accumulating of ground information related to forestry characteristics;

- simultaneous processing of aerospace and ground information;
- analyzing the results and forecasting the prospects of forest development, including the consequences of forestry activities.

A review of literature sources showed a large number and variety of works related to various types of monitoring, as well as the development of schemes and maps of disturbances of different categories of land. To solve the problem of interpretation of forest lands damaged by various adverse factors, the works of a number of researchers were considered (Lyalko et al., 2004; Forest monitoring for Europe, 2009; Kuemmerle et al., 2009). Various interpretation methods are used for monitoring, which is reduced to the following:

- visual (analytical);
- measuring;
- analytical and measuring;
- automated.

To improve the visual perception of images, the use of simply derived indices is practised. To study and highlight the boundaries of the post-fire stand, various vegetation indices are widely used. Simple NDVI and SWVI indices are used to divide forest areas into damaged and undamaged; however, the middle and near-IR spectra are the most informative, so the SWVI index is the most reliable.

The following scientists are dealing with the problems of assessing the impact of man-made load on the environment and research in this direction using geographic information systems and remote sensing technologies of the Earth: O.S. Alekseev, I.A. Vukolova, V.O. Glagolev, O.S. Isayev, Norchevsky, I.L. Tsebenko, H.V. Burshtynska and among foreign scientists: J.R. Anderson, J. Ardo, W.J. Carper, T.M. Lillesand, D.L. Civco, F.M. Gemmill, etc. However, recognizing the scientific and practical value of the developments of mentioned authors, it should be noted that the problem of introducing remote sensing data (RSD) in the forest fire monitoring system is far from complete and requires deep systematic study.

Although there are many scientific publications on the use of remote sensing methods and GIS technologies (Sakhatsky et al., 2002; Richards and Xiuping, 2005) for monitoring forest resources: general, specifically on the use of GIS-technologies, and remote sensing methods or their combination in some specific area of research. The authors of this article consider it necessary to cover this topic more thoroughly.

Scientists from all over the world are receiving a lot of attention from the application of methods of uncontrolled and controlled classification of space images for forest monitoring. At present, these methods are being improved, combined to improve the quality of classification. Interesting works on the application of the classification of space images Sentinel-2 and Landsat are presented in scientific papers (Abadi and Grandchamp, 2008; Ganz et al., 2020; Hatwell et al., 2020; Liu et al., 2020).

The boundary of the research area was defined as follows: Nyzhankovychi – Strilkovychi – Boryslav – Bolekhiv – Novoselytsia – Lyuta – Lopushynytsia – Nyzhankovychi. The total area of the study territory is 583 241 hectares (Fig. 1).

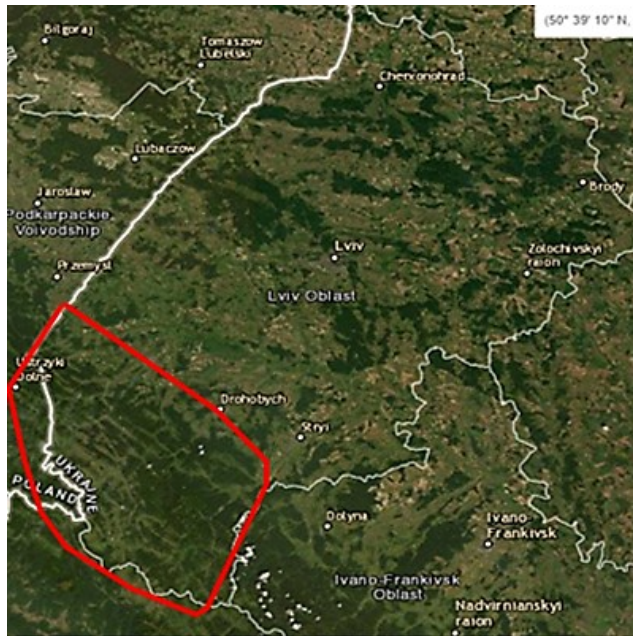


Fig. 1. Selected research region

## 2. Materials and methods

We used space images obtained from the Landsat-8 satellite over three years to more accurately study the area of deforestation in the Carpathian territory, as well as to trace the trend of such deforestation. Landsat-8 providing moderate-resolution imagery, from 15 metres to 100 metres, of Earth's land surface and polar regions, Landsat 8 operates in the visible, near-infrared, short wave infrared, and thermal infrared spectrums. Landsat 8 captures more than 700 scenes a day, an increase from the 250 scenes a day on Landsat 7. The OLI and TIRS sensors will see improved signal to noise radiometric (SNR) performance, enabling 12-bit quantization of data allowing for more bits for better land-cover characterization (Landsat, 2021).

The input data for the task were the following images:

- LC08\_L1TP\_186026\_20161002\_20170403\_01\_T1 – image on 02/10/2016;
- LC08\_L1TP\_185026\_20171016\_20171024\_01\_T1 – image on 16/10/2017;
- LC08\_L1TP\_186026\_20181010\_20181030\_01\_T1 – image on 10/10/2018.

All images were downloaded from the site of the American Geological Survey in the projection UTM WGS84 zone 34, units – meters.

The workflow of studies is presented in Figure 2. To fulfil the task of determination the forest area of the Carpathian territory of Lviv region by space images for three years with an interval of one year, it is necessary to implement a band composition procedure. For Landsat-8, the best band composition for the determination of forest cover is a composition of 5, 4 and 3 bands. This combination of information is mainly

used to study the health of vegetation and water bodies. Water objects in its application are displayed in tints of dark and light blue color depending on the depth, etc. Healthy vegetation is manifested in tints of green and from orange to brown. Bright blue tints can reflect recently felled forests and red tints – poor vegetation. The average IR band increases the distinction of stages of growth of plants and their stresses. This composition is not recommended for the study of man-made structures such as roads and runways and should be used with caution in interpretations, especially if the survey was carried out immediately after precipitation. Like the band composition 451, this combination provides the user with an extensive amount of information and color contrast.

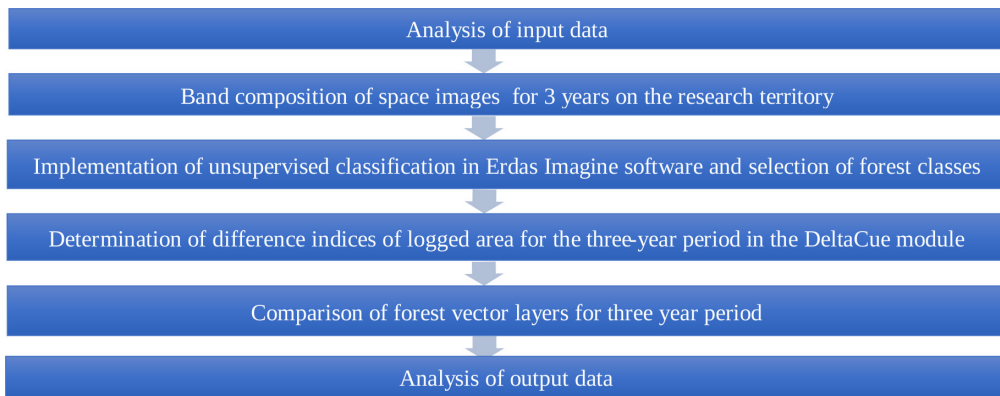


Fig. 2. The workflow for the determination of areas of deforestation in the Carpathian territory of the Lviv region

The most common methods of classification of space images are supervised and unsupervised classification, classification based on the knowledge base, segmentation and cluster analysis, etc. Unsupervised classification is performed automatically and depends only on the information in the image. It makes it easy to distinguish objects when identifying a relatively small number of classes. It gives excellent results when such test plots are selected that can be verified by reliable ground data, or when well-marked, homogeneous areas representing each class can be identified. On the other hand, if it is necessary to create classes according to the spectral differences inherent to pixels. Then unsupervised classification will be more expedient for this task. It makes it easy to distinguish an infinite number of such classes (groups of pixels). An unsupervised classification can be useful for creating a thematically defined set of classes using the following supervised classification. A combination of unsupervised and supervised classifications (hybrid) gives optimal results, especially for large data sets.

Algorithms of unsupervised classification allow the user to set some parameters. The computer uses these parameters to detect spectral (including statistical) features of digital image data. The areas with such features do not correspond to the objects; they are simply groups of pixels with similar spectral characteristics. Unsupervised classification algorithms implement clustering methods often used in various multidimensional studies, which are based on the so-called boundary procedures. Their application assumes that



the amount of input information suffices to separate classes and therefore etalons are not used. During image processing, these algorithms apply various ranges of class separation of objects features and form the mathematical basis for their formal classification.

During boundary classification, the brightness values of two adjacent pixels are compared. If the difference in brightness values exceeds a certain predetermined value (threshold), it is assumed that these pixels belong to different objects and between them, there is the boundary line. In the case of a multispectral image, the thresholds are set either for the brightness differences of each spectral band or for the distances of features that are used as a measure of the boundary. Using this method, the accuracy of classification is not high, but when the absence of a priori information about the classes the implementation of such procedure is appropriate because it gives the possibility to distinguish homogeneous brightness areas (subclasses) of objects based on their natural differences in spectral brightness. When objects of any class are described by vectors whose components are real numbers, this class can be considered as a cluster and its properties can be distinguished in the image space of the cluster.

To implement the classification of space images, we need to define the parameters by which the algorithm will assign image pixels to a specific user-defined class. This process is called the creation of class signatures and is performed based on field data (etalons, training data) and photo interpretation. Often during the formation of class signatures, errors can occur due to the assignment of pixels to an unusual class, which reduces the accuracy of classification.

Erdas Imagine can perform classifications that are both time-consuming and quick to perform. This classification (according to the ISODATA algorithm) is based on the use of the formula for the least spectral distances. We use this classification method when the spectral features of different classes are similar and the ranges of their brightness values overlap. Average values of classes are pre-determined.

Thus, the pixel is assigned to that class in which distance to the set of average values is the least. This process takes place in several stages (iterations). During each iteration, all pixels are reclassified and new averages are selected for the clusters for which the distances are determined. As a result, all pixels in the image are distributed among classes.

Uncontrolled classification algorithms allow the user to set some parameters that the computer uses to detect the inherent digital data of images of spectral (including statistical) images. These images do not necessarily correspond to the subjects; they are simple groups of pixels with similar spectral characteristics.

Uncontrolled classification algorithms implement clustering methods often used in various multidimensional studies, which are based on so-called boundary procedures. Their use assumes that the amount of source information is sufficient to separate classes and therefore standards are not used. When processing images, these algorithms apply various measures of class separation in the feature space of objects and form the mathematical basis of their formal classification.

In general, the limit classification compares the brightness values of two adjacent pixels. If the difference in luminance values exceeds a predetermined value - the threshold,

it is assumed that these pixels belong to different objects and between them there is a separation limit. In the case of a multi-band image, the thresholds are set either for the brightness differences of each spectral band, or for the distances in the space of features that are used as a measure of resolution. In this way, the accuracy of classification is low, but in the absence of a priori information about the classes of such a procedure is appropriate, because it can be used to distinguish homogeneous brightness areas (subclasses) of objects based on their natural differences in spectral brightness. When objects of any class are described by vectors whose components are real numbers, this class can be considered as a cluster and its properties can be distinguished in the space image of the cluster.

To classify space images, you need to define the parameters by which the algorithm will assign image pixels to a specific user-defined class. This process is called the creation of class signatures and is performed on the basis of field data (standards, training data) and photo interpretation. Often during the formation of class signatures, errors can occur due to the assignment of pixels to an unusual class, which reduces the accuracy of classification.

Erdas Imagine has the ability to conduct classifications with and without training. Classification without training is less time consuming and quick to perform. This classification (according to the ISODATA algorithm) is based on the use of the formula for the smallest spectral distances. This method of classification is used in the case of similarity of spectral features of different classes and overlapping ranges of values of their brightness. The average values of the classes are determined in advance. Thus, the pixel belongs to the class whose distance to the set of averages was the smallest. This process takes place in several stages – iterations. At each iteration, all pixels are reclassified and new averages are selected for the clusters to which the distances are determined. As a result, all image pixels are distributed between classes.

We allocated only the researched part of the image, namely the Carpathian territory of the Lviv region, to reduce the cost of computer time when performing the classification (Fig. 1). To identify the research area, we used the corresponding tool for allocation of an area of interest (AOI). We set the following parameters in the classification settings window:

- the path to the synthesized image (syntezovani.img);
- the path and name of the resulting file (class2016.img);
- the path and name of the signature file to be created (class2016.sig);
- classification method and data source (Isodata, Initialize from Statistics);
- number of created classes (15);
- number of iterations planned to be held in automatic mode (25 – recommended in the literature for the classification of forest cover);
- convergence threshold (0.95).

Also, the path to the AOI file is specified separately to perform the classification only for the planned part of the image, by clicking on the AOI button.



### 3. Results

The result is a classified part of the image for the Carpathian territory of the Lviv region interpreted in 15 classes, and one class contains unclassified pixels. Since our task was only to allocate a layer of forest stands to compare it over the years, we allocated only two classes: first – the class of “forest stands” and second – the class for the rest of the territory. In the window for editing the attributes of the classified file, we temporarily change the color of the classes corresponding to the forest cover to make it easier to identify the pixels (Fig. 3).

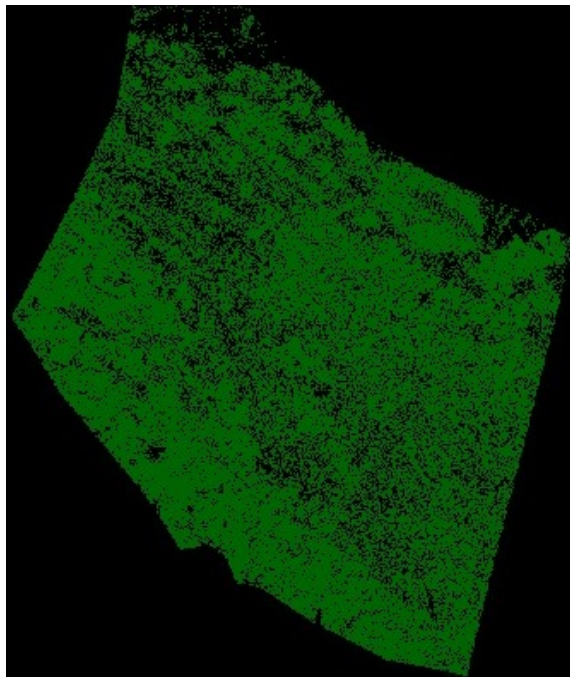


Fig. 3. Classified area of the research with changed colours of classes related to forest cover

All classes were grouped into a common forest cover group, except for classes 0, 2, 8, 10, 12, which did not belong to the forest class. At the bottom of the dialogue window, we enter the value 1 in the field New Value and change the class number for the selected lines. This operation allows to combine the selected classes into one common class - forest objects.

After these actions, the proportion of red, green and blue colors for classes will be changed in the attribute table of the classified image, namely for the class of wood the red and blue colors will have value 0.

To calculate the area of a forest class, it is necessary to convert this class from bitmap to vector form. We perform all the same actions as described above for the images of 2017 and 2018. The obtained results are presented in Figures 4 and 5.

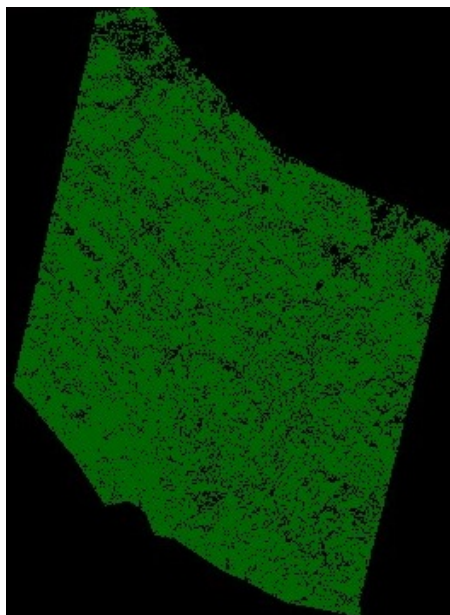


Fig. 4. Classified area of the research on the image of 2017

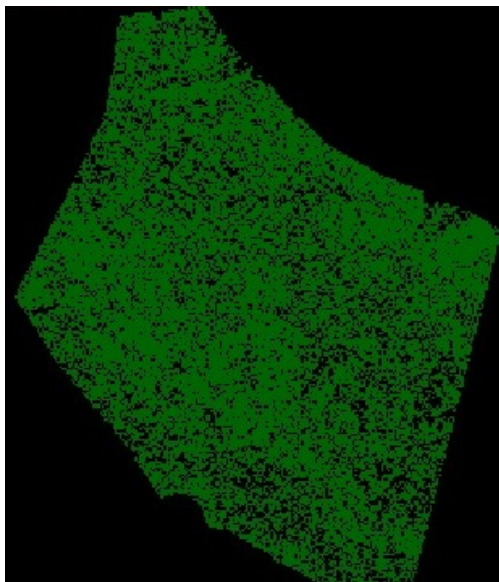


Fig. 5. Classified area of the research on the image of 2018

Analyzing the obtained histograms of classified images of 2016, 2017 and 2018, it is seen that the largest changes occurred in 2, 4, 6, 7, 8, 10, 11 and 14 classes. Considering that 4, 6, 7, 11 and 14 classes belong to the forest cover, these are quite serious changes.

Table 1 presents the area of classified forest cover for 2016–2018 calculated by the corresponding vector layers.

Table 1. Areas of forest cover of the Carpathian territory of Lviv region for 2016–2018

	Image 2016	Image 2017	Image 2018
Area of the forest (ha)	538 467.0	538 459.0	538 448.0

As it is seen from the table, the area of forest decreased by 19ha comparing the data of 2016 and 2018. Since, in the absence of verification information for this area, we do not use the method of supervised classification, and the method of unsupervised classification gives rather rough results, it was decided to use the DeltaCue module to search changes over three years.

There is an additional module IMAGINE DeltaCue in Erdas Imagine software for determining object changes, which allowing detect differences between two images of the same area, taken at different times. Due to the dynamic setting of change thresholds, as well as spatial or spectral filtering, the module allowing display only those changes that are interesting for the user. Data processing and analysis in DeltaCue are organized in the form of projects that involve the following sequence of actions:

- preprocessing;
- detection of changes;
- filtering of detected changes;
- display and analysis of changes.

The image differencing is formed automatically in the DeltaCue Erdas Imagine module, by applying formula (1) sequentially to all the corresponding pixels in pairs in each of the spectral bands:

$$d' = S_1 \cdot DN_2 - S_2 \cdot DN_1, \quad (1)$$

where  $DN_1$  and  $DN_2$  are the pixel values in the corresponding spectral bands of the images No. 1 and No. 2,  $S_1$  and  $S_2$  are the mean arithmetic values of  $DN$  in each of the spectral classes.

The larger the value of  $d'$  modulo, the greater the changes that have occurred in the area and vice versa. Two compared images must be geometrically and spectrally identical. For achieving the best results, we use DeltaCue functions for image normalization. The widest arsenal of methods can be used to detect changes using satellite images of different time obtained by one type of sensor in similar survey conditions. In addition, the use of such a combination of data is most effective in terms of the variety of changes that occur.

Then we choose the method of fixation of changes. The most active methods are *TC Green Diff* – based on the detection of vegetation groups. The next step is to select the filters for further elimination of unwanted changes. In this dialogue, you can control three types of change filters:

- spectral segmentation;
- incorrect registration of pixels of image pair;
- spatial filtering.

Making sure that the mode *Spectral Segmentation* is switched on – this is a prerequisite for a quality search for change, we activate the *Field Misregistration* (incorrect registration of pixels of image pair), and the *Field Spatial Filtering* leave for a while inactive. It provides settings for spatial filters, which allows to select certain objects that have changed according to spatial criteria. The result of the obtained difference indices is given in Figure 6. After analyzing the obtained data, it was found that many objects are erroneous or obtained in the form of noise during filtering.

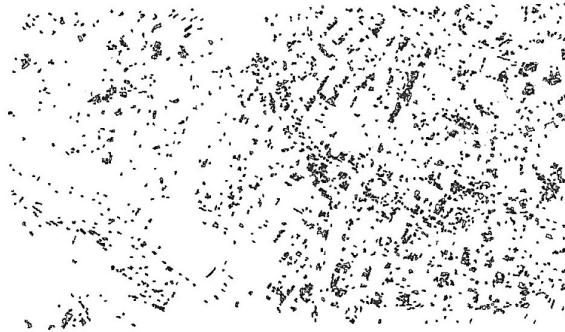


Fig. 6. Fragment of the vector layer of the different indices of forest cover changes according to the images of 2016 and 2018

In the next operation, we will search for changes using all filters, adding a spatial filter. It calculates several geometric properties based on the contour line. The geometric properties include:

- area;
- the length of the main axis;
- the length of minor axes;
- compactness;
- prolongation.

For our case, we use geometric properties: area, compactness and prolongation. The result of the search for changes is presented in Figure 7.

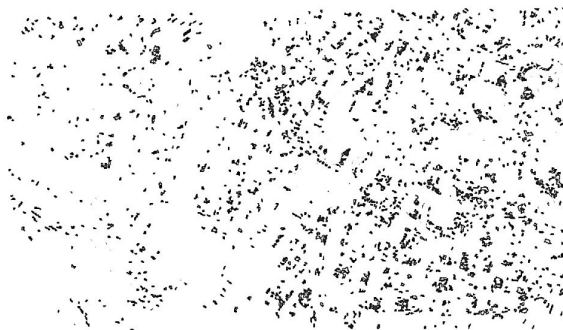


Fig. 7. Fragment of the vector layer of the different indices of forest cover changes according to the images of 2016 and 2018 obtained using all filters

After the application of all filters, we get a vector layer of objects with a total area of 18.6 hectares, which is close to 19 hectares, obtained early by the method of unsupervised classification. In each of the methods, the percentage of felling for 3 years is 0.1%.

#### **4. Conclusions**

According to official data, the total area of the Lviv region is 2 183 100 hectares, and the forested part of it is about a quarter, then the obtained data of forest cover are quite reliable. As can be seen from Table 1, the area of forest plantations compared to 2016 in 2017 decreased by 8 hectares. The area of forest plantations in 2018 compared to 2017 decreased by 11 hectares. That is, the forest area of the Carpathian territory of Lviv region for 3 years from 2016 to 2018 decreased by 19 hectares. Given the trends and speed of deforestation in the Carpathians, we can assume that this is the reason for the decrease in area. We cannot assess whether there was lawful felling or not, as we do not have information on planned deforestation. Analyzing the accuracy of determining the forest cover according to the performed classification, we chose a test site of logged territory, which is present in all images with size  $238 \times 93$  m. The area of this site is 2.2 hectares, which is 0.00032% of the total area, the area of the same site in another image is 0.00031%, i.e. the difference in the area is 0.00001% in relative percentages, which is a satisfactory value for this surveying system, as the area of one pixel is  $100 \text{ m}^2$ . The obtained values of the areas are quite approximate because there were used the images of average spatial resolution and the method of unsupervised classification, and not, for example, the supervised classification.

#### **Author contributions**

Conceptualization: B.Ch.; methodology development: I.T.; writing – original draft: L.B.; writing – review and editing: M.M.

#### **Data availability statement**

The raw/processed data required to reproduce these findings cannot be shared at this time as the data also forms part of an ongoing study.

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