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Remote sensing monitoring of changes in forest cover in the Volyn region: a cross section for the first two decades of the 21st century

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ABSTRACT

The aim of the article. This article highlights the significance of forest cover as an important indicator of the state of the environment. It discusses the findings of the Food and Agriculture Organization of the United Nations (FAO) Forest Resources Assessment (FRA) 2020 report, which states that the world's forest area has decreased by 178 million hectares since 1990. The case study of Volyn region shows how cloud processing and vegetation classification can help quantify forest dynamics from 2000 to 2020, allowing local authorities and decision makers to monitor and analyze trends in near real time. Overall, this work provides insights into the importance of monitoring forest dynamics and the potential for remote sensing technology to facilitate this process.

Data & Methods. Remote sensing is an effective tool for monitoring forest ecology and management, and Google Earth Engine (GEE) is an online platform that combines data from various agencies to analyze environmental data. The article presents a case study of the Volyn region and how cloud processing and vegetation classification were used to assess forest dynamics from 2000 to 2020. The study used data from Landsat 7 Collection 1 Tier 1 composites and the CART algorithm for binary decision tree building. The study was based on information provided by the Main Department of Statistics in the Volyn region on the area of forests and areas where logging was carried out during the specified period.

Research results. It is interesting to note that despite the decrease in logging activities, there is an increase in forest cover loss within forest ranges. This could be due to various reasons, such as illegal logging or natural disturbances like fires or disease outbreaks. The use of machine learning methods like CART classification can help to identify and monitor these changes, which can then be used to inform policy decisions and management practices to reduce forest cover loss. In general, in the Volyn region, there is a gradual decrease in the areas where various kinds of logging are carried out from 524 km^2 in 2003 to 239 km^2 in 2020. In contrast, forest cover loss within forest ranges increased rapidly from 37.85 km^2 in 2015 to 84.01 km^2 in 2017 and beyond from 5.53 km^2 to 10.80 km^2 in 2015 and 2017 respectively. In this study, the accuracy assessment was performed using 30% of the control points obtained initially, based on data on the reliability of the land cover. The manufacturer's accuracy and user accuracy were calculated to evaluate error omissions and possibilities of a pixel being categorized in a certain category. The spatial resolution of Landsat 7 data used in this study was 30 m, with a minimum calculation area of 0.337 hectares. The overall accuracy and the coefficient κ are the most representative measures of accuracy, with an average accuracy of classification of OA_{av}=98.82% and κ_{av}=0.9764.

***Keywords**: forest dynamics, remote sensing, Google Earth Engine, machine learning, CART algorithm, forest cover loss, accuracy assessment, Landsat 7.*

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Introduction. One of the most important indicators of the state of the environment is forest cover. According to the Food and Agriculture Organization of the United Nations (FAO) Forest Resources Assessment (FRA) 2020 report [1], since 1990, the world's forest area has decreased by 178 million

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hectares, which is roughly the size of Libya. The rate of decline in net forest area declined markedly between 1990 and 2020 as a result of reduced deforestation in some countries and an increase in forest area in others due to afforestation and natural forest expansion. The rate of decline in net forest area decreased from 7.8 million hectares per year between 1990 and 2000 to 5.2 million hectares per year between 2000 and 2010 and 4.7 million hectares per year between 2010 and 2020. Over the past decade, net forest area loss has slowed at a slower pace due to the share and distribution of the world's forest area and the slowdown in forest expansion.

Popular remote sensing methods used in environmental research, and in particular forests, are images of the Earth's surface obtained with the help of various sensors installed on aircraft and space platforms. Remote sensing is used to map the distribution of forest ecosystems, fluctuations in vegetative productivity of plants, study their biomass, health, reconstruct their three-dimensional (3D) structure, etc.

Remotely sensed images provide a view of the Earth's surface and allow for the decoding and characterization of objects on it. Moreover, it is usually possible to obtain images of a certain area repeatedly in time, which allows for monitoring in near-real time. As a result, remote sensing is used in a diverse range of forest ecology and management applications, from mapping invasive species [2] to monitoring land cover changes such as habitat fragmentation [3] to assessing biophysical and biochemical properties of forests [4].

Remote sensing data are becoming better and more accessible to a wider audience of users every year, which facilitates their use in environmental research. The temporal and spatial synchronization of observations over large areas has significantly improved the quality and quantity of environmental observation data. More detailed spatial and temporal monitoring of the earth's environment is becoming possible due to the increased availability of satellite images. In particular, a series of satellite optical data with high spatial resolution from Landsat 5-7, Sentinel-2 and synthetic aperture radar data from RADARSAT, Sentinel-1 allow for monitoring studies with an accuracy that meets or significantly exceeds traditional methods and, accordingly, mapping of these changes.

Thanks to the Earth observation sensor, it captures the full picture of the environment in the imaging band. The resulting image gives a complete picture of the object that comes into view. Thus, every visible object is recorded, including its location and position relative to all other objects in the imaged area, giving the images a map-like format that provides a complete survey of the imaged area, unlike field data, which is often based on a very limited set of samples that must be generalized using some form of interpolation. With this complete survey, remote sensing allows for continuous mapping and monitoring of important environmental variables such as changes in forest cover.

Remote sensing data is available for virtually the entire surface of the globe, everywhere and often at different spatial and temporal scales. Key environmental remote sensing systems, such as the Landsat satellites, have been providing a continuously updated stream of images of the entire planet since the 1970s. The availability of optical imagery regardless of location allows, in particular, to study objects, no matter how remote or inaccessible they may be. In addition, historical remote sensing data allows us to go back in time and look at the dynamics of various natural and anthropogenic processes.

Remote sensing images have a high degree of homogeneity. Importantly, the data of key remote sensing systems are obtained under relatively fixed conditions, and the data obtained relate to the way radiation interacts with the environment, which is constant in space and time. This eliminates errors caused by the human factor.

On a per-area basis, remote sensing is an inexpensive way to acquire data. Although the financial costs associated with remote sensing can sometimes be very high, many of them are freely available. In recent years, there has been a growing trend towards free and open access to key datasets for scientific research. For example, the full archive of the influential Landsat series of satellites is freely available, and the European Space Agency (ESA) has recently launched a number of new satellites and is making the data collected free of charge.

An important advantage of remote sensing imagery is that it can be easily integrated with other spatial data sets in a geographic information system.

Per unit area, remote sensing is an inexpensive way to acquire data. Although the financial costs associated with remote sensing can sometimes be very large—for example, it is expensive to build, launch, and operate satellite remote-sensing systems, making some imagery expensive—much is freely available. Additionally, although commercial remote-sensing systems can appear costly, the data still provide inexpensive assessment on a unit-area basis. More critically, however, there has been an increasing trend to make key datasets for environmental science research freely and openly available. For example, the complete archive of the influential Landsat series of satellites is freely available, and recently the European Space Agency (ESA) launched a suite of new satellites and provides the data collected for free.

Analysis of the latest research and publications. The forests in the five countries were studied using remote sensing from MODIS and MERIS satellites in comparison with land cover maps at the European level [5, 6], laser remote sensing, digital aerial photography, and space sensor data at the global level [7, 8]. Landsat data were used to calculate changes in forest cover between 1985 and 2012 for Bosnia and Herzegovina, Croatia, Montenegro, and Slovenia [9]. These countries were included in European and global studies using Sentinel satellite imagery and LUCAS Copernicus in-situ observations [10] and land cover maps [11]. At the country level, changes in forest cover between 1991 and 2011 and grassland in Croatia have been determined [12]. At the country level, various remote sensing systems such as LiDAR, close-range remote sensing data for measuring tree canopy and height in forests was used at works [13, 14]. MODIS data have been used to analyze vegetation and orthophotographs to identify invasive plant species in anthropogenic and semi-natural areas of Slovenia [15], as well as forest canopy structure in old-growth forests of Bosnia and Herzegovina [16]. In Ukraine, the study of deforestation detection in the forest-steppe zone for the Kharkiv region was discussed in [17], Forest inventory and biomass mapping fro region of Polissya [18], assess the extent of illegal logging and reforestation in the Ukrainian Carpathians [19][20]. Current study is logical continuation of research started in determining forest species of Volyn region using supervising classifications methods [2, 21, 22]

Separation of the unsolved part of the whole problem. One of the problems of analyzing data with high spatial resolution on a large scale (for example, research at the country or regional level) is the huge amount of data that needs to be downloaded and processed. For example, Landsat and Sentinel satellite data, which are commonly used to monitor vegetation from local to global scales, require a huge number of datasets to cover the areas.

Currently, the processing of large arrays of high-resolution images requires the ability to simultaneously spatially and temporally aggregate a collection of satellite images without experiencing problems with information technology, high variability, and data availability.

Goal formulation of the paper. GEE (Google Earth Engine) is an online platform for analyzing environmental data that combines data from various agencies such as the National Aeronautics and Space Administration (NASA) and the Landsat program. Google provided the ability to use its cloud computing resources to record and process Landsat images through its online system after the US Geological Survey opened access to Landsat image records in 2008. This allows users to reduce processing time when analyzing Landsat images and make global-scale Landsat projects easier to implement [23].

The 30-meter spatial and multispectral resolution of Landsat is optimal for monitoring environmental changes on a local scale, and the current viewing time is sufficient for monitoring land cover change [24]. From 1972 to the present, Landsat has been a popular platform used to analyze land cover changes, including urban and vegetation cover [25, 26]. Therefore, the use of GEE helps us to quickly analyze global data [27].

We chose to use GEE in this study because GEE allows us to process large remote sensing data sets and other ancillary data sets on a cloud computing platform. Earth Engine is accessed and controlled through a web-based application programming interface (API) and an associated web-based interactive development environment (IDE) that allows for rapid prototyping and visualization of results.

The purpose of this study is to analyze the state of forest cover and its changes in Volyn using GEE and to demonstrate how effective GEE is for monitoring large areas. Using the GEE platform, we tried to estimate forest cover in 2000-2020 and compare the dynamics of changes with official statistics. In addition, we discussed the feasibility of GEE for analyzing the monitoring of forest cover change at the regional and national scales.

To achieve this goal, the following main research objectives had to be fulfilled:

1. Identify and assess the change in forest cover within the Volyn region during 2000-2020 using open access data;
2. Determine whether there is a difference in forest cover loss in forest areas of different departmental subordination and those that do not belong to them;
3. Compare the obtained data with statistical data.

Presentation of the major research material. National Forest Inventory and Monitoring Systems (NFIMS) is a tool that allows you to obtain data on the above criteria and indicators at the national and regional levels, and track trends. Accordingly, the criteria and indicators for sustainable forest management should define the main indicators of the NFIMS and the assessment of forest resources. According to the results of national forest inventories and monitoring, on average once every 5 years, all European countries provide results on criteria and indicators of sustainable forest management (according to the Helsinki process) [28, 29], and some countries, such as Canada, the United States and others, according to criteria and indicators according to the Montreal Process for Boreal Forests [30]. Ukraine has committed itself to support the Helsinki process (Forest Europe) [31].

The need to reform environmental monitoring is envisaged by the Decree of the President of Ukraine dated 18.10.2013 No 572 "On the decision of the National Security and Defense Council of Ukraine of April 25, 2013" On a set of measures to improve environmental monitoring and state regulation in the field of waste management in Ukraine". In addition, the Decree of the President of Ukraine dated 21.11.2017 No. 381 provides for the need to improve the state environmental monitoring system and introduce a national forest inventory (NFI) in Ukraine.

In Ukraine, preparations have begun for the introduction of a national forest inventory (NIL) based on selective-statistical methods on a network of permanent plots in accordance with the Instruction developed by scientists of the laboratory for monitoring and certification of forests of UkrNDILGA together with specialists of PA "Ukrderzhlisproekt"[32].

However, to date, Ukraine has not yet approved a national list of criteria and indicators of balanced development, although scientific research on this issue has been conducted [33]. The existing national system for collecting data on forests today does not allow obtaining information on all indicators. To assess the balanced management of forests in Ukraine, there are data obtained from the results of state accounting of forests and forest cadastre, which relate to forest area, forest cover of the territory and timber reserves [34]. The introduction of a system of national inventory and forest monitoring will make it possible to obtain such data at the regional level, and in the future – at the state level.

In the presented work, we applied a state-of-the-art machine learning algorithm on Google Earth Engine (GEE) [23], a cloud computing service, to estimate almost 20 years of forest evolution using satellite multispectral imagery. In recent years, GEE has become a valuable platform where researchers from various fields can deploy their models [34,35,36]. In addition, GEE provides access to a data catalog with various global products, as well as the latest satellite observations from NASA's Landsat and the European Space Agency's (ESA) Sentinels missions. In addition to near-real-time data distribution, users have access to images in a wide time range, allowing them to select the most appropriate ones for temporal analysis. As a result of GEE implementation, three problems previously mentioned in the literature were successfully overcome: GEE, with its huge data catalog and computing power, reduces the time to identify relevant data and the actual processing time, and ensures high quality and reliability of image classification.

As a case study, the territory of Volyn region was chosen and the forest dynamics from 2000 to 2020 was assessed in one-year increments. With the help of cloud processing, it was easy to identify the most suitable cloudless satellite products and perform the necessary vegetation classification, which allowed to quantify the processes of loss and gain. The results of this work will help local authorities and decision makers to not only monitor forest dynamics in near real time, but also to analyze how these trends will develop in the future.

In the Volyn region, there are 696,000 hectares of forest lands, with 62% classified as forests of state importance, 37.5% as forests belonging to agricultural enterprises, and 0.5% as forests belonging to other users. The forests are further divided into two groups based on their economic significance, namely protective forests and operational forests, which respectively account for 23% and 77% of the state reserve. The current forest cover in the region is at 34.6%, with the highest concentration of forest cover found in the Manevychi district (65% of its territory) and Kamin-Kashirsky district (41%). The dominant types of forests in the region are conifers, which make up 60% of the forests, followed by mixed forests (birch, aspen) at 24%, and hardwood forests at 16%. The forest resources in the region are considerable, comprising 16.2% of the total National Resource Potential (NRP) and exceeding the national average value by four times.

The main factors affecting forest dynamics include:

1. Illegal logging, which is one of the biggest problems in the region. This leads to a decrease in the volume of forest plantations and loss of biodiversity. Unfortunately, despite the efforts of the authorities to combat this problem, illegal logging continues.

2. Volyn's forests are also attacked by various pests and diseases that reduce their productivity and survival. A particularly serious problem is caused by the pest bark beetle, which destroys wood and leads to its loss as an economic resource.

3. Forest fires pose a serious threat to forest plantations in Volyn Oblast. Fires destroy large areas of forests and other natural resources, as well as pollute the air and harm human health.

4. Excessive deforestation, air and water pollution, and other human activities can lead to the destruction of ecosystems, which reduces biodiversity and forest productivity.

Materials. This paper is based on data from Landsat 7 Collection 1 Tier 1 composites which are made from Tier 1 orthorectified scenes, using the computed top-of-atmosphere (TOA) reflectance. These composites are created from all the scenes in each 8-day period beginning from the first day of the year and continuing to the 360th day of the year.

The last composite of the year, beginning on day 361, will overlap the first composite of the following year by 3 days. All the images from each 8-day period are included in the composite, with the most recent pixel as the composite value.

Methods. Using binary decision trees for classification is a nonparametric approach to pattern recognition. The decision tree provides a hierarchical representation of the feature space in which x_i samples are distributed into classes w_j $(j = 1,2,...,k)$ in accordance with the result obtained as a result of executing decisions made in a sequence of nodes in which the branches of the tree diverge. The type of decision tree used in this work is discussed in detail in the work [35], whose contribution has been summarized to the CART (Classification And Regression Trees) algorithm.

This pointing technique is that trees can be used not only to classify objects into a discrete number of groups, but also as an alternative approach to regression analysis, in which the value of the response variable (dependent) must be evaluated taking into account the value of each variable in the set of explanatory (independent) variables. Binary decision trees consist of multiple division of the feature space into two subspaces, with end nodes associated with w_j classes. A desirable decision tree is one that has a relatively small number of branches, a relatively small number of intermediate nodes from which these branches diverge, and a high predictive force in which objects are correctly classified at end nodes.

CART involves identifying and building a binary decision tree based on a sample of training data for which the correct classification is known. The number of objects in the two subgroups defined on each binary partition corresponding to the two branches emanating from each intermediate node decreases sequentially, so that a sufficiently large training sample is required to obtain good results [36].

The decision tree begins with the root node t, which comes from which a variable in the feature space minimizes the degree of admixture of two related vertices. Using the definition given in [35], the measure of impurity in the node t, denoted by $i(t)$, has the form, as shown in the following equation (1),

$$i(t) = -\sum_{j=1}^{k} p(w_j \mid t) \log p(w_j \mid t) \qquad (1)$$

where $p(w_j \mid t)$ – part of the patterns x_i, assigned to class w_j at the top t.

Each nonterminal vertex is then split into two subsequent vertices, t_L and t_R, so that p_L, p_R are fractions of entities passed to new vertices t_L and t_R, respectively. The best partition is one that maximizes the difference given in (2):

$$\Delta i(s,t) = i(t) - p_L i(t_L) - p_R i(t_R) \qquad (2)$$

The decision tree grows by successive divisions until a stage is reached at which there is no significant reduction in the degree of impurity with further additional separation s. When this stage is reached, the vertex t is not divisible further and automatically becomes the terminal vertex. The class w_j associated with the terminal node t is a class that maximizes the conditional probability $p(w_j \mid t)$.

Training samples. Based on vector data of afforestation plans, obtained in response to the request of the State Forest Agency of Ukraine, 46 certification areas covered with forest vegetation were selected and verified in Landsat 7 images as of 2000 and 2020. To determine non-forest-covered areas, 35 polygons were selected that correspond to the characteristic widespread landscapes of the Volyn region.

Results. At the request of the authors of the article, the Main Department of Statistics in the Volyn region provided information on the area of forests in the Volyn region according to the Derzhgeocadastr and areas where logging was carried out during 2000-2020 (Fig. 1 and Fig. 2). This information covers the territories subordinated to the State Forest Agency of Ukraine and does not include other users, territories of forest protection strips, parks, self-forested areas, agricultural lands with perennial plantations, etc.

First of all, we analyzed the area of forest vegetation with a height of more than 5 m in general, on the territory of the Volyn region, as well as its loss in the period from 2000 to 2020, according to the methodology proposed above. Forest cover losses were calculated as a change in the forest-nonforest class based on the annual remote sensing data obtained (Fig. 3). Based on the data obtained, areas of forest cover loss both within forestry and beyond were calculated (Fig. 4).

Accuracy assessment. During the implementation of controlled classification, a number of errors occur due to spectral similarity of classes or user errors in determining certification areas. For this purpose, an assessment of the accuracy of land cover classification was carried out to determine and measure the error values of the resulting image. The most common method for assessing accuracy is the calculation of the error matrix [16], in which the data of the obtained image are compared with the control data for the corresponding number of classification units. Accordingly, on the basis of the obtained error matrix, the overall accuracy of the classification is calculated as the ratio of correctly classified elements to the total number of sample elements.

The accuracy assessment was used to verify the classification by using 30% of the control points obtained initially. The reference value entered by the researcher is based on data on the reliability of the land cover. In this classification, manufacturer's accuracy (includes error omissions referring to the degree of observed aspect on terrain that is not classified on the map) and user accuracy (evaluates error omissions and explains the possibility that a pixel is categorized in the category). Due to the use of Landsat 7 data with a spatial resolution of 30 m, the average minimum area for which calculations can be made is 0.337 hectares.

The error matrices were calculated to assess the accuracy of land use classes and land cover. There are four specific statistical measures of accuracy, namely Overall accuracy (OA), Producer accuracy (PA), User accuracy (UA), and κ, which were obtained to assess classification accuracy. The most representative of these are the total accuracy (OA) and the coefficient κ. The average accuracy of classification is OA_{av}=98.82%, $κ_{av}$=0.9764. The assessment of accuracy for each year is presented in Fig. 5.

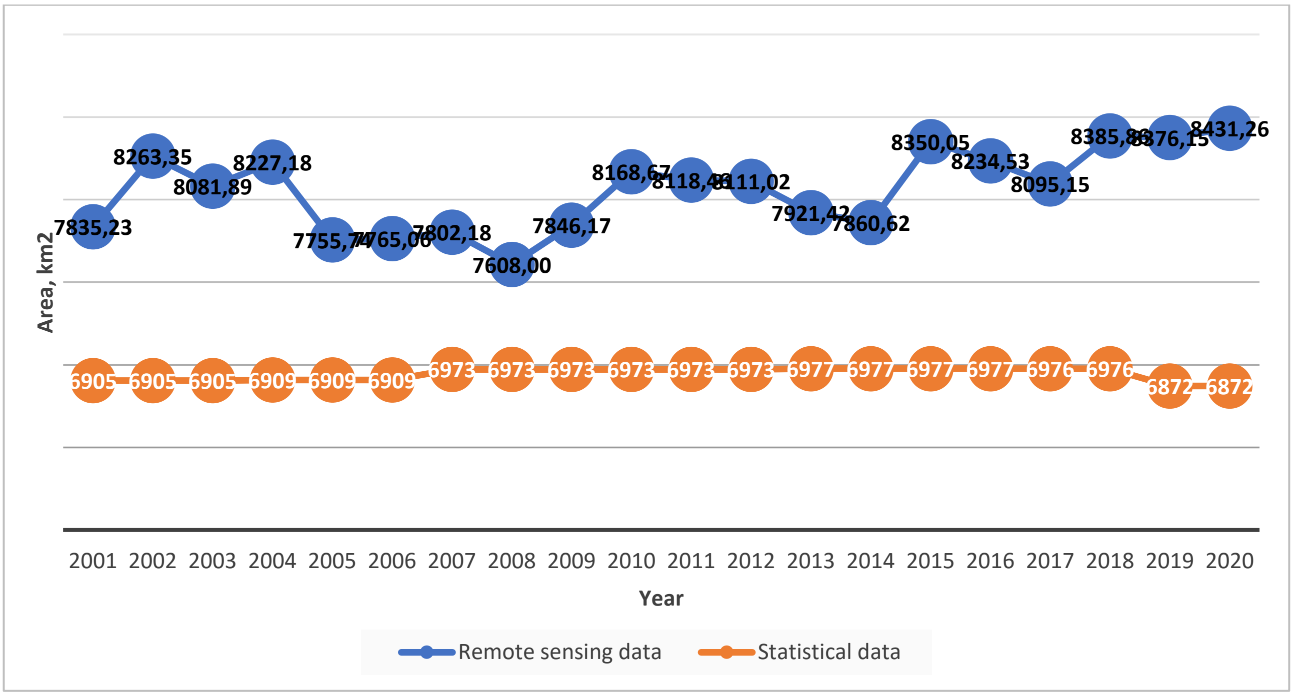

Fig.1. Forest areas according to remote sensing data and statistics data

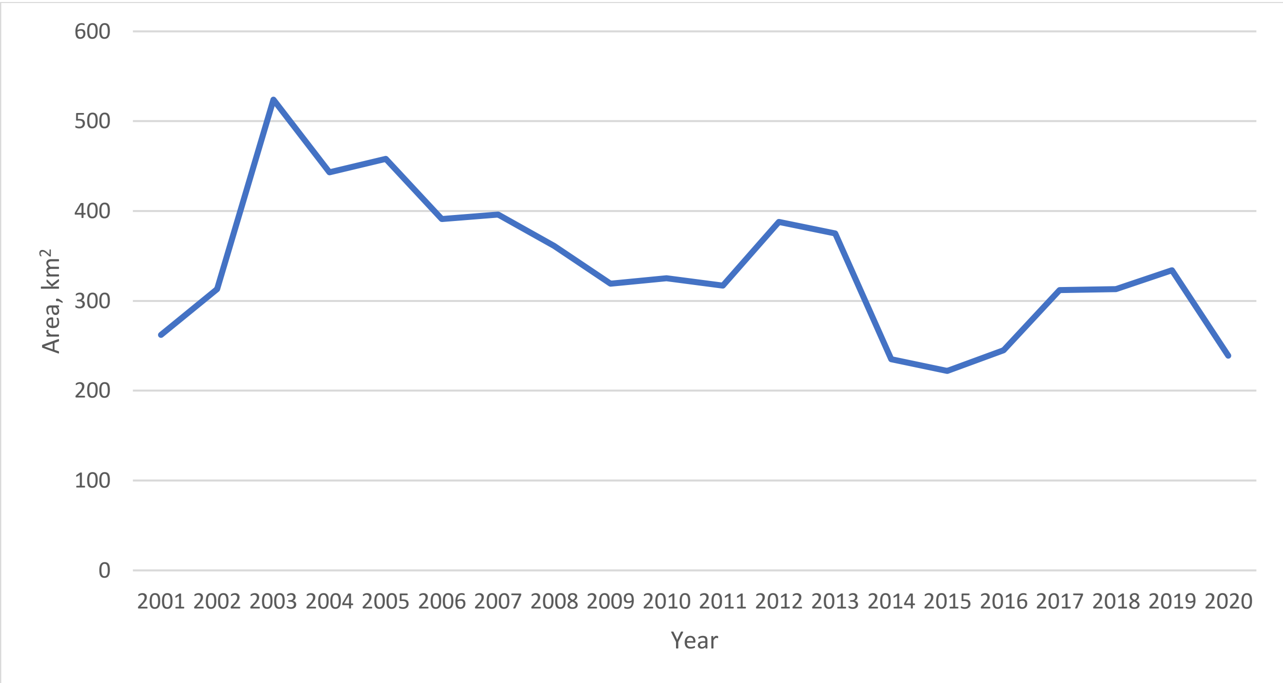

Fig. 2. Area on which logging was carried out during 2000-2020 according to the statistics department

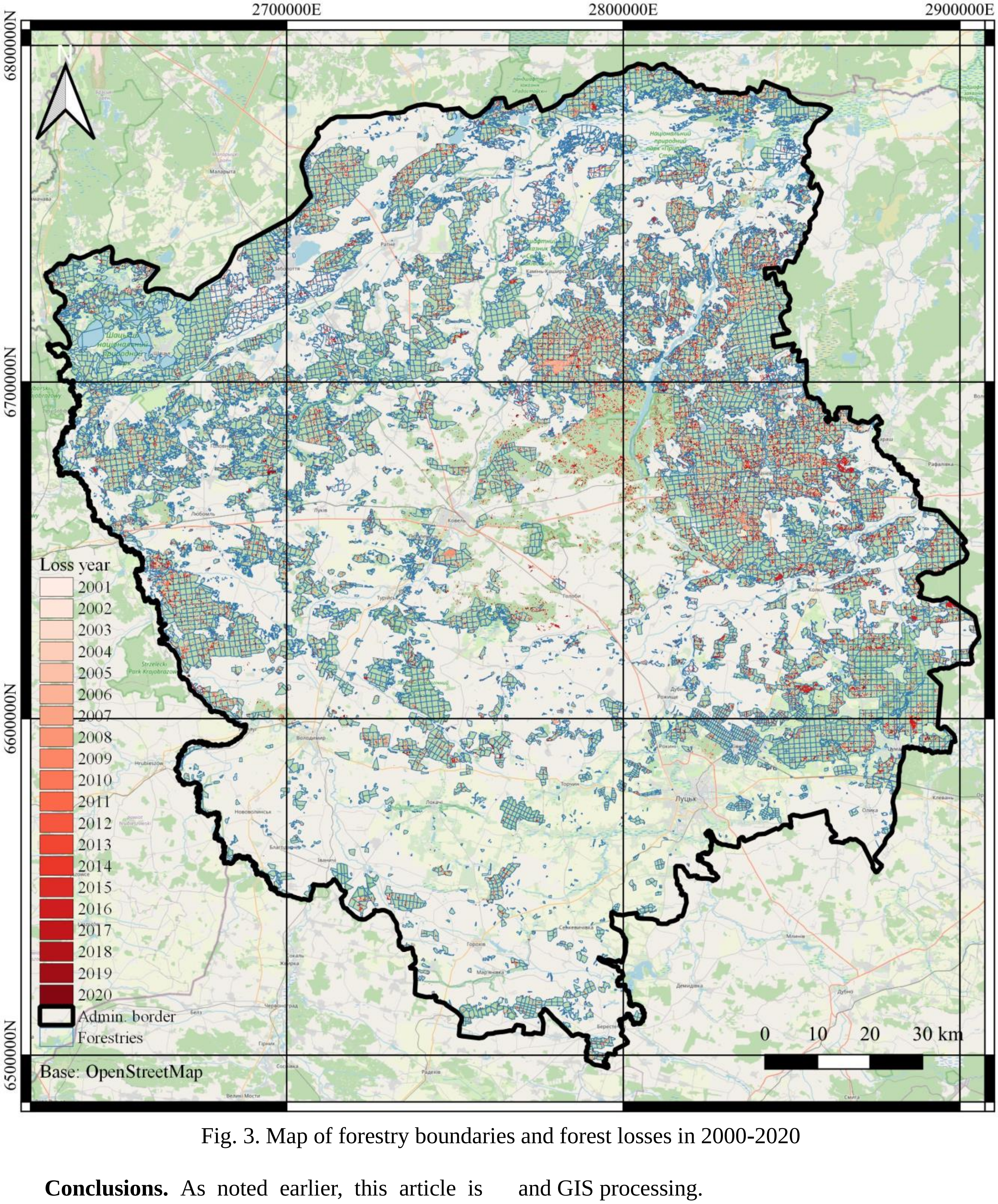

Fig. 3. Map of forestry boundaries and forest losses in 2000-2020

Conclusions. As noted earlier, this article is devoted only to the temporal changes in the forest-covered areas of the Volyn region during 2000-2020. All data/images were obtained, processed and analyzed on the GEE platform based on Landsat images with a spatial resolution of 30 m.

This paper also attempted a large-scale analysis of forested areas on a cloud platform to measure and quantify changes and draw the necessary conclusions about its effectiveness. Overall, GEE has proven to be an excellent tool and alternative to commercial software and services for remote sensing and GIS processing.

The results of the CART classification have confirmed their popularity and effectiveness as a machine learning method. The high accuracy of the algorithm was largely due to the careful selection of verification areas.

Based on the results obtained, it was found that there are large discrepancies with official statistics and remote sensing data. This may be due to insufficient statistical accounting of forested areas of both different land users and unaccounted areas and their representation in statistical reports. Depersonalizati-

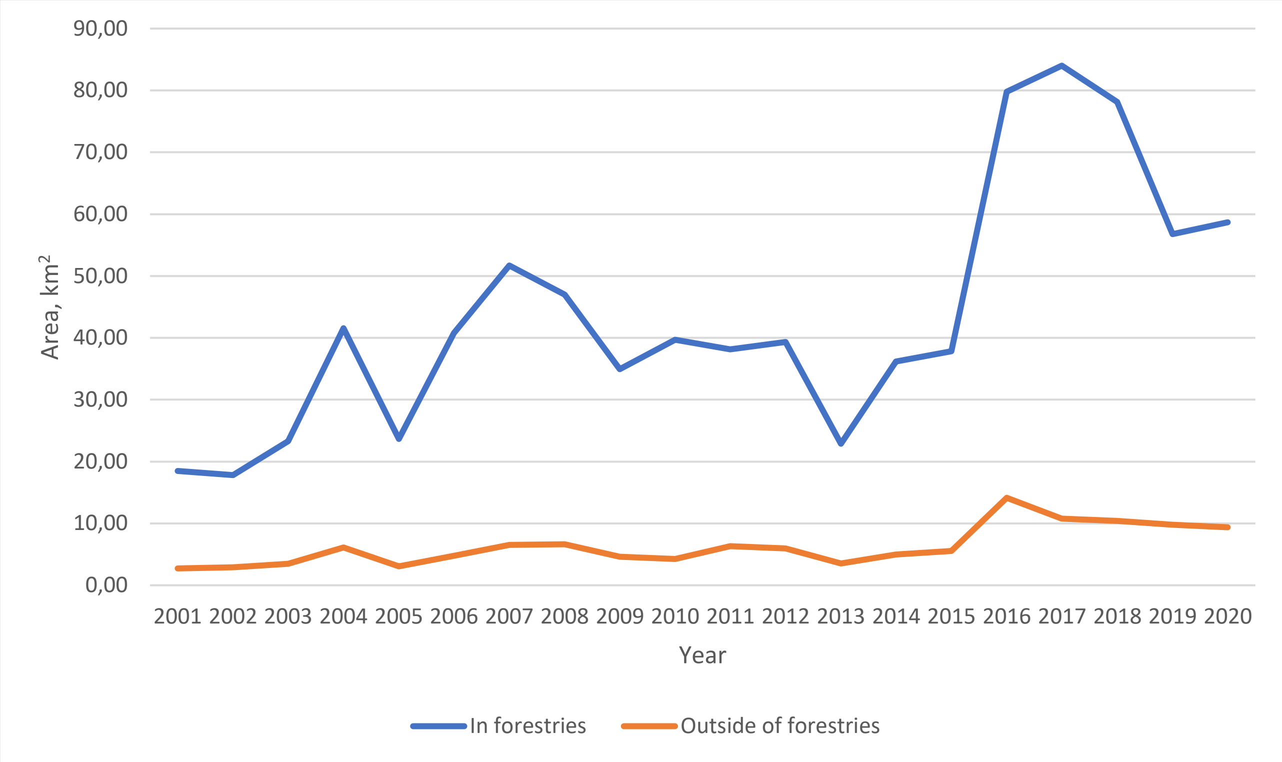

Fig. 4. Distribution of areas of losses within forestries and beyond

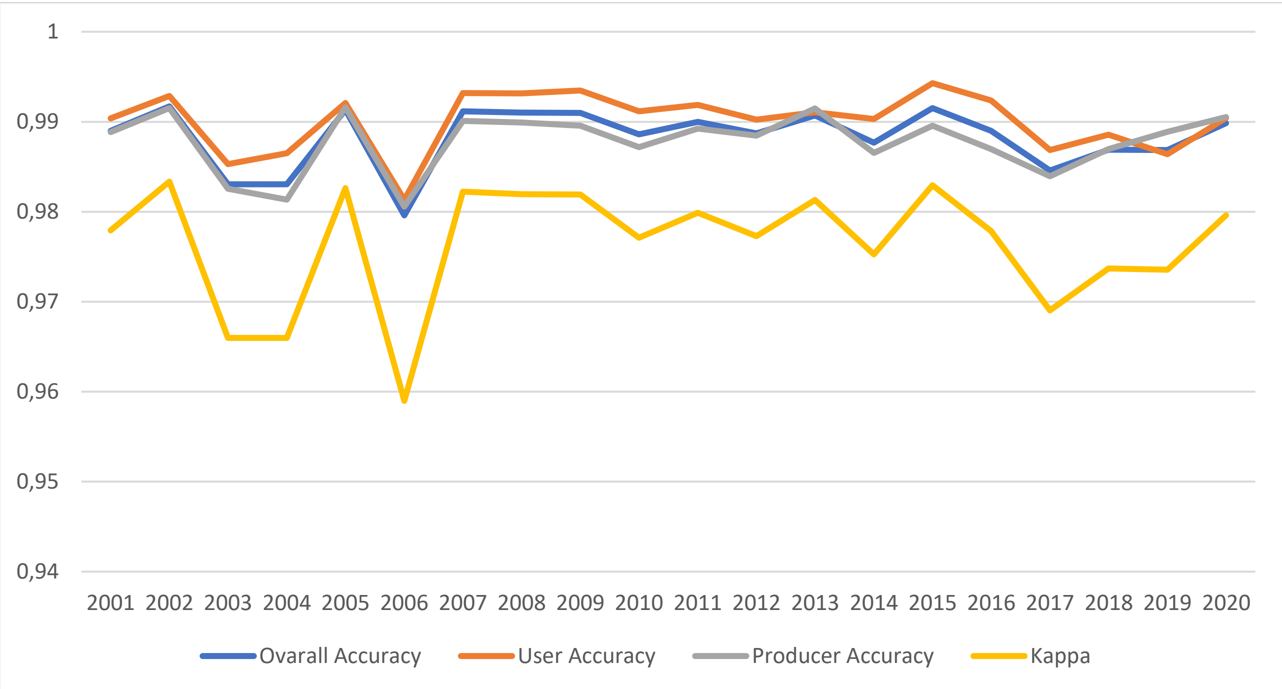

Fig. 5. Accuracy assessment

on of statistical data does not allow monitoring individual forestries by remote methods and comparing real loss indicators.

In general, in the Volyn region, there is a gradual decrease in the areas where various kinds of logging are carried out from 524 km^2 in 2003 to 239 km^2 in 2020. In contrast, forest cover loss within forest ranges increased rapidly from 37.85 km^2 in 2015 to 84.01 km^2 in 2017 and beyond from 5.53 km^2 to 10.80 km^2 in 2015 and 2017 respectively.

For future work, it is recommended to combine object-oriented classification (OBIA) and determination of spectral indices of different forest age groups and species composition. In turn, this requires a more careful selection of verification areas with their fixation by GNSS. Also, for a more detailed analysis of individual areas, it is advisable to use remote sensing data from Sentinel-2 optical sensors with a spatial resolution of 10 m and weather-independent radar data sensors Sentinel-1. The proposed technique allows for near real-time monitoring due to the high temporal repeatability of probing the territory by different sensors. These steps will be highlighted in further research.

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Дистанційний моніторинг змін лісистості Волинської області: зріз за перші два десятиліття XXI ст.

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У статті висвітлюється значення лісистості як важливого індикатора стану навколишнього середовища. Згідно доповіді Продовольчої та сільськогосподарської організації ООН (FAO) щодо оцінки лісових ресурсів (FRA) за 2020 рік, в якій зазначено, що з 1990 року площа лісів у світі скоротилася на 178 мільйонів гектарів. На прикладі Волинської області показано, як обробка даних дистанційного зондування із використанням хмарних сервісів і класифікація рослинності можуть допомогти кількісно визначити динаміку лісів з 2000 по 2020 рік, дозволяючи місцевій владі та особам, які приймають рішення, відстежувати та аналізувати тенденції майже в режимі реального часу. Загалом ця робота дає зрозуміти важливість моніторингу динаміки лісу та потенціал технології дистанційного зондування для полегшення цього процесу. Дистанційне зондування є ефективним інструментом для моніторингу та управління лісами, а Google Earth Engine (GEE) – це онлайн-платформа, яка об'єднує дані від різних установ для аналізу різного роду даних. У дослідженні використано дані Landsat 7 Collection 1 Tier 1 та алгоритм CART для побудови бінарного дерева рішень. Дослідження базувалося на інформації Головного управління статистики у Волинській області про площі лісів та площі, де проводилися рубки протягом зазначеного періоду. Слід відзначити, що незважаючи на зменшення територій на яких здійснюється лісозаготівля, спостерігається збільшення втрати лісового покриву в межах лісових масивів. Це може бути викликано різними причинами, такими як незаконна вирубка лісу або природні порушення, як-от пожежі чи спалахи хвороб. Використання методів машинного навчання, таких як класифікація CART, може допомогти виявити та відстежувати ці зміни, які потім можна використовувати для інформування про рішення та методи управління для зменшення втрати лісового покриву. Загалом у Волинській області спостерігається поступове зменшення площ, де проводяться різні види рубок, з 524 км^2 у 2003 р. до 239 км^2 у 2020 р. Натомість втрати лісистого покриву в межах лісових масивів стрімко зросли з 37,85 км^2 у 2015 р. до 84,01 км^2 у 2017 р., а за межами з 5,53 км^2 до 10,80 км^2 у 2015 р. та 2017 р. відповідно. У цьому дослідженні оцінка точності проводилася з використанням 30% контрольних точок, отриманих початково, на основі даних про достовірність земельного покриву. Точність виробника та точність користувача були розраховані для оцінки пропусків помилок і можливостей віднесення пікселя до певної категорії. Просторова роздільна здатність даних Landsat 7, використаних у цьому дослідженні, становила 30 м, з мінімальною площею розрахунку 0,337 га. Загальна точність і коефіцієнт κ є найбільш репрезентативними показниками точності, із середньою точністю класифікації OA_{av}=98,82% і κ_{av}=0,9764.

Ключові слова: *динаміка лісів, дистанційне зондування, Google Earth Engine, машинне навчання, алгоритм CART, втрата лісового покриву, оцінка точності, Landsat 7.*

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