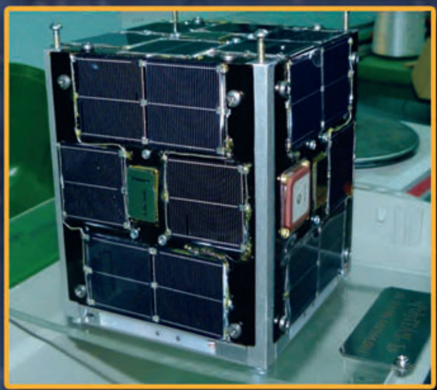
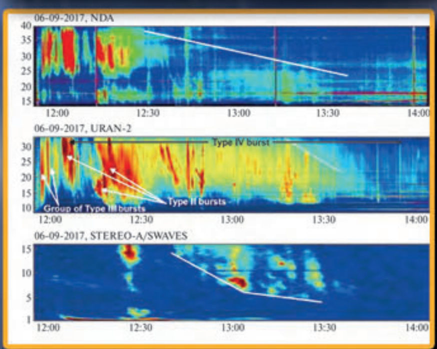
SPACE RESEARCH IN UKRAINE

2022–2024





NATIONAL ACADEMY OF SCIENCES OF UKRAINE

SPACE RESEARCH IN UKRAINE

2022—2024

Report
to COSPAR

The Report Prepared by the Space Research Institute of NAS of Ukraine and SSA of Ukraine

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Report to COSPAR summarizes the results of space research performed during the years 2022—2024. This edition presents the current state of Ukrainian space science in the following areas: Space Astronomy and Astrophysics, Earth observation and Near-Earth Space Research, Life Sciences, Space Technologies and Materials Sciences. A number of papers are dedicated to the creation of scientific instruments for perspective space missions. Considerable attention paid to applied research of space monitoring of the Earth. The collection can be useful for a wide range of readers, interested in space research.

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CONTENTS

INNOVATIVE APPROACHES FOR FOREST MONITORING USING REMOTE SENSING AND CLOUD COMPUTING

N. Kussul [1, 2, 3], A. Shelestov [1, 2], B. Yailymov [1], H. Yailymova [1, 2], M. Lavreniuk [1], L. Shumilo [3], S. Skakun [3], V. Kuzin [2], N. Salii [1, 2], A. Kolotii [1, 2]

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Introduction

This article presents advanced methods for forest monitoring using remote sensing data, computational machine learning techniques, and cloud computing platforms. The work focuses on three main research directions: 1) Intelligent feature engineering for semantic segmentation of damaged forest areas from satellite imagery using genetic algorithms [1—5]; 2) Intelligent analysis of forest cover change dynamics in conflict zones based on time-series satellite imagery [6]; 3) Semi-automated mapping of European forest types with high resolution using the Google Earth Engine cloud platform [7—9]. The results demonstrate the effectiveness of the developed approaches in detecting damaged forest areas, assessing the impact of military actions on forest vegetation, and creating up-to-date maps of forest vegetation types across Europe.

The first part of the study introduces an automated feature selection method using genetic algorithms for semantic segmentation of forest diseases from satellite imagery. This approach includes numerical evaluation of individual features and their combinations, along with a simplified representation of vegetation indices to facilitate feature set optimization. The framework enhances feature engineering for earth observation, enabling precise identification of forest health degradation with minimal labeled data.

The second part aims to explore the impact of militarized occupation of natural protected areas and the subsequent interruption of conservation efforts on ecosystem sustainability. By analyzing time-series satellite imagery before, during, and after the conflict, the study quantifies and evaluates policies and processes underlying the establishment of the Emerald Network in the Luhansk region of Ukraine. The results indicate that the separation of ecosystems from environmental protection institutions and policies through the occupation of territory led to dramatic deforestation and loss of ecosystem sustainability.

The third part focuses on mapping European forest types by harnessing the power of high-resolution Sentinel-1 and Sentinel-2 satellite data from the Copernicus program. The novelty lies in the integration of various data sources for training dataset creation and the utilization of the Random Forest classifier on the Google Earth Engine cloud computing platform. The resulting forest type map for 2022 has a fine spatial resolution of 10 meters and distinguishes between broadleaved, coniferous, and mixed forests, with an impressive overall accuracy of 93%.

This research demonstrates the potential of synergizing cutting-edge remote sensing, machine learning, and cloud computing technologies to tackle complex environmental challenges at a continental scale. The developed methodologies pave the way for future advancements in forest disease monitoring, fire danger, conservation efforts, and environmental impact assessment, empowering informed decision-making in sustainable forest management.

Feature Engineering for Semantic Segmentation of Forest Diseases

Remote sensing techniques leveraging satellite imagery are increasingly utilized for environmental monitoring tasks such as land use classification and assessment of vegetation health. In particular, semantic segmentation methods based on machine learning have recently attracted much attention for their ability to delineate geographical regions of interest in satellite imagery. However, while these techniques have been extensively studied for various applications, such as land cover mapping and urban development analysis, the task of forest health monitoring [5], particularly the fire danger monitoring [11, 12], identification of bark beetle-induced damage, remains relatively novel.

Our study aims to address the following research questions:

1) How to effectively define and optimize feature informativeness and independence for semantic segmentation of forest diseases?

2) Does computational feature engineering improve segmentation accuracy and increase model robustness compared to utilizing spectral bands of satellite imagery?

To deal with the research questions we introduce an automated feature selection method using genetic algorithms that eliminates the need for model training. This approach includes a numerical evaluation of individual features and their combinations, alongside a simplified representation of vegetation indices for easier feature set optimization. Our framework enhances feature engineering for earth observation, especially in identifying forest diseases.

We have defined two key study areas for our investigation. The primary area, located in the Grand Est region of France, includes satellite images and corresponding stress

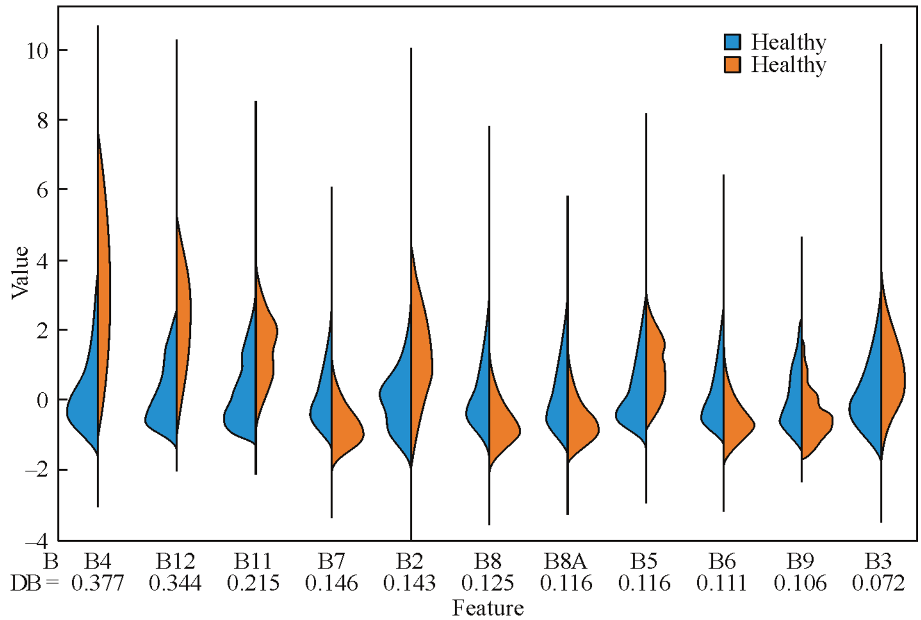

Fig. 1. Violin plot of spectral bands used and their individual informativeness (DB)

masks that delineate areas of forest under stress. The project provided us with the Dataset 1, which comprises 60 sites of damaged forests, totaling 385,637 coniferous forest pixels, of which 7% exhibit signs of stress. For the purposes of model training and validation, we divided these sites so that both the training and validation datasets contained a nearly equal proportion of stressed pixels. The training set includes 28 sites, featuring 13,017 stressed and 189,608 healthy pixels, whereas the validation set encompasses 32 sites, with 13,868 stressed and 169,144 healthy pixels.

To assess the robustness and general applicability of our models, we also incorporated a second study area located in the Chornobyl Exclusion Zone, Ukraine, utilizing 2018 satellite imagery. This area serves as an additional dataset for visual analysis to evaluate model performance (Dataset 2), although it is important to note that comprehensive labelling of stressed coniferous areas is not available for this dataset.

We use Sentinel-2 multispectral images as input data. As is known, such images contain information about the Earth's surface in different spectral bands, which allows us to use them for various purposes, such as land cover monitoring, vegetation measurement, and detection of environmental changes. Also, we have used vegetation indices — quantitative indicators used to measure and analyze plant growth and health based on the spectral properties of vegetation. As well as vegetation indices are quantitative state estimates and can be designed to distinguish objects from others, they serve (along with spectral bands) as features for segmentation. Since vegetation indices are mathematical functions, we propose to use a more generalized concept — a class of vegetation indices — to facilitate work with them. A detailed description of the methodology for the formation of informative features using the Bhattacharya distance is described in detail in the works [1—3].

Violin plots (Fig. 1) for features from the top-performing BANDS, MCARIbased, FRAC3, and HUESIMP models show the distribution across healthy and stressed labels, with feature values normalized using RobustScaler trained on healthy forest data. Fig. 1 suggests the most discriminative bands are Red (B4) and SWIR (B11-B12), while other bands are less informative. Fig. 1 indicates that selected features are more informative, albeit with some decreasing trends.

The segmentations by the models based on MCARIbased (Fig. 2, *b*), FRAC3 (Fig. 3, *a*), and HUE (Fig. 3, *b*) were largely consistent, with MCARIbased occasionally identifying non-forest areas as stressed. The segmented areas, viewed against the ground truth in Fig. 4, *b*, tended to overestimate stressed regions. Yet, comparing the RGB image in Fig. 4, *a* with the segmentations in Fig. 3, it's noticeable that areas classified as stressed have a distinct, lighter, and more brownish hue, potentially signaling imminent stress. This suggests a mild over-sensitivity in the models, possibly stemming from inaccuracies in the training data or a need for finer threshold adjustments for classifying forest health.

The segmentation outcomes (Fig. 2, 3) suggest the need for suitable augmentation during model training, favoring complex convolutional networks over pixel-based approaches, or relying on vegetation indices like HUE that are resistant to constant noise.

Model robustness was tested on Dataset 2 (Ukraine), with segmentation results shown in Fig. 6. The images in Fig. 5, normalized like in Fig. 4, *a*, display significant brightness variations, emphasizing the importance of accounting for brightness differences in feature selection and model training. Segmentation analysis (Fig. 6) suggests a high stress level across the coniferous forest. However, BANDS (Fig. 6, *a*) and MCARIbased (Fig. 6, *b*) models yielded noisy outcomes, while FRAC3 (Fig. 6, *c*) and HUE (Fig. 6, *d*) models were less noisy but HUE misclassified many non-coniferous areas as stressed. This was expected since the models were trained solely on coniferous forest data without a forest type mask. The models' sensitivity led to most forests being marked as

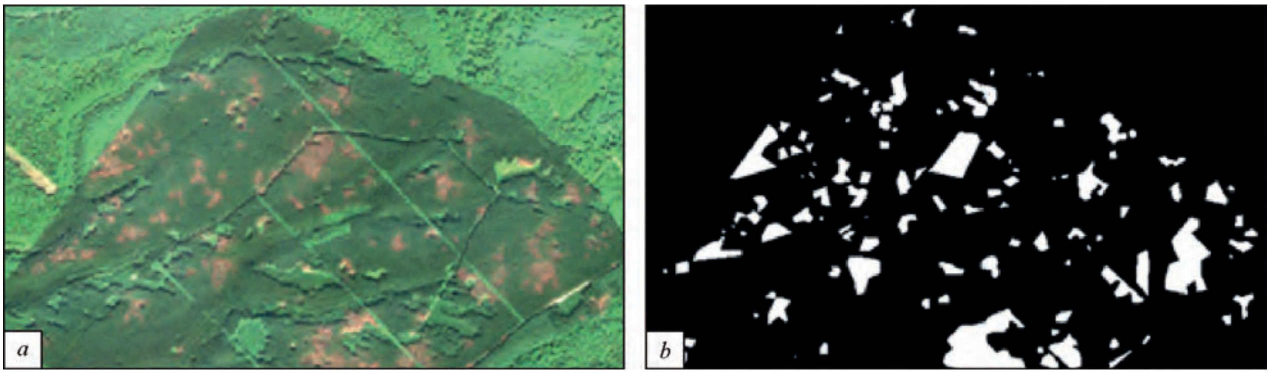

Fig. 2. Results of segmentation of test site of Dataset 1 by *a* — BANDS, *b* — MCARIbased models

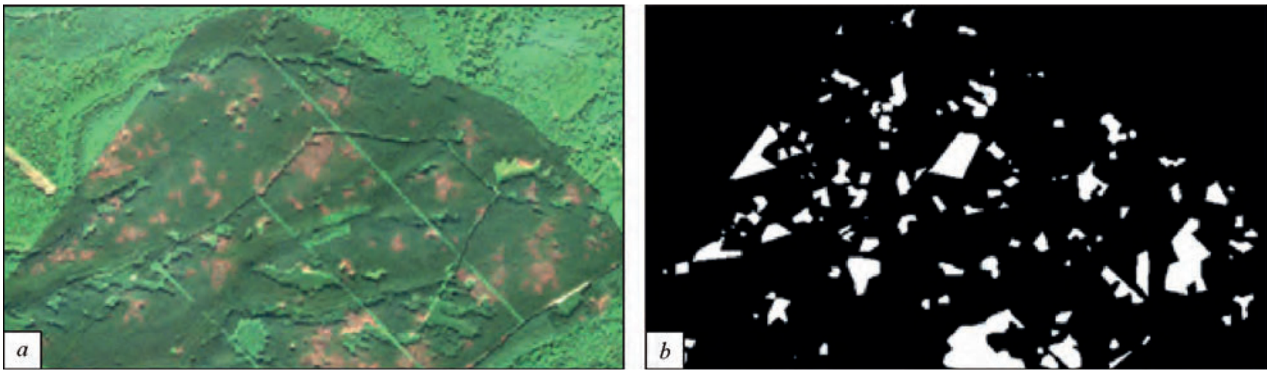

Fig. 3. Results of segmentation of test site of Dataset 1 by constant noise independent *a* — FRAC3, *b* — HUE models

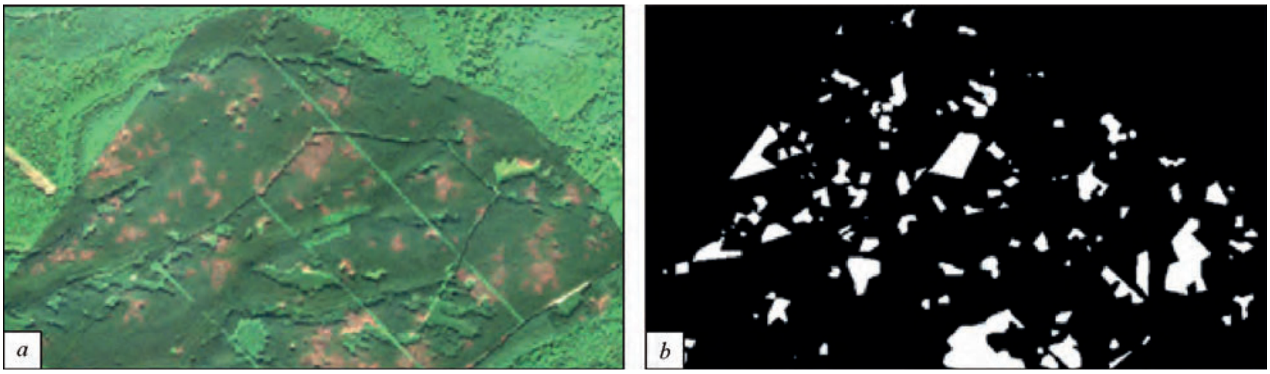

Fig. 4. Dataset 1 test area: *a* — RGB Sentinel-2 image, *b* — ground truth mask

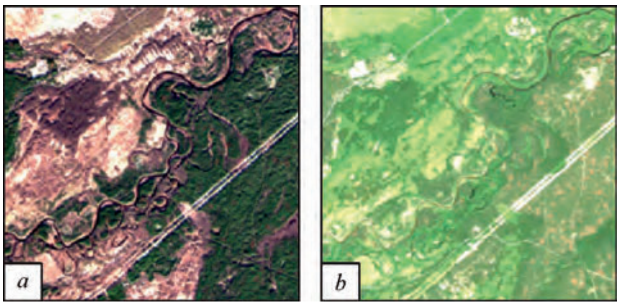

Fig. 5. Sentinel-2 images for Dataset 2 test area during winter (*a*) and summer (*b*) of 2018

stressed, which was later confirmed by experts, especially visible in the light brown tint of the forest in Fig. 5, *b*.

This research illustrates that leveraging optimized feature engineering with vegetation indices can notably enhance the semantic segmentation of satellite forest imagery over traditional spectral band usage [1—3]. By employing specialized informativeness and independence functions along with genetic algorithms for feature selection, we achieved high-quality models without compromising accuracy. Vegetation indices resilient to brightness variations proved especially effective in maintaining segmentation quality despite significant differences in image brightness between

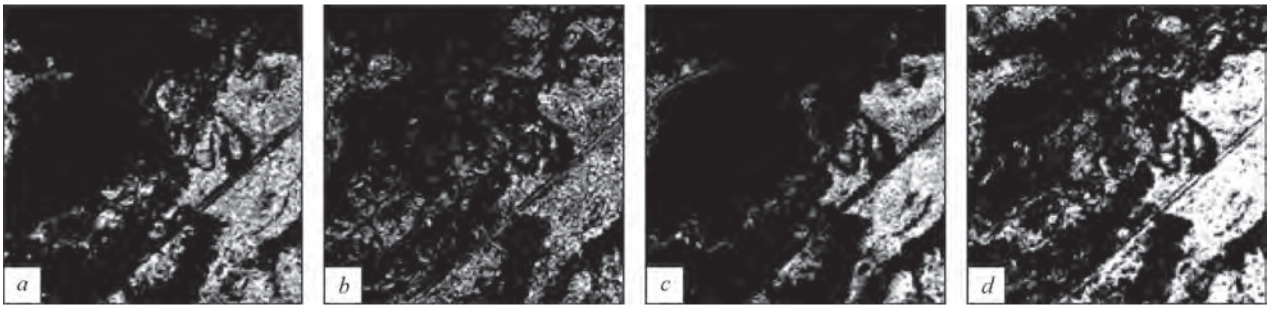

Fig. 6. Results of Dataset 2 test area segmentation by BANDS (*a*), MCARIbased (*b*), FRAC3 (*c*), HUE (*d*)

training and test datasets, addressing a common challenge with spectral bands and conventional indices [4]. We introduced novel approaches to feature engineering in remote sensing, such as mathematical definitions for feature informativeness and independence that facilitate numerical feature set optimization, and the use of generative classes for vegetation indices to bypass the need for manual index enumeration. These methodologies, particularly the introduction of brightness-invariant index classes, demonstrated consistent segmentation results across varying image conditions. These techniques can significantly aid in large-scale forest monitoring, enabling precise detection of health degradation with minimal labelled data [5]. To expand the research area and detailed analysis of forest health, we created a data set for machine learning for the territory of Ukraine [13].

Methods of intellectual analysis of the dynamics of forest cover change in Ukraine

The war has inflicted a range of harms on the socio-ecological system which are very likely to have lasting socio-ecological impacts. Assessing the environmental consequences of these events is nearly impossible due to the lack of physical access to these areas. To these ends, we aimed to explore the impact of the militarized occupation of natural protected areas and the subsequent interruption of conservation efforts on ecosystem sustainability. Such research can be conducted only using long-term observations before the military conflict and after the hot phase of the conflict and the establishment of a stable demarcation line. Due to the active warfare in 2022 and 2023, it is premature to quantify ecosystem conservation consequences. Thus, we focused on the progress of the Emerald Network establishment in the Luhansk region (Fig. 7) in terms of land cover changes in the environmental protection zones from 1996 to 2020 [6].

Quantification and evaluation of policies and processes underlying the establishment of Emerald Network in the Luhansk region was conducted by analyzing forest cover changes trends in the territories on both sides of the conflict demarcation line established after the "Minsk-2" and "Misnk-3" agreements in 2014 and 2015. Utilizing the principles of deforestation pressure-based management regime comparison, we evaluated the effectiveness of the Bern Convention's conservation policies and examined the

Fig. 7. Emerald Network sites in Luhansk region separated by demarcation line. The gray hashed area represents territory under Russian control after 2014 with an established demarcation line in 2015. The hashed area represents Emerald Network sites established on the blanks of Siverskyi Donets river

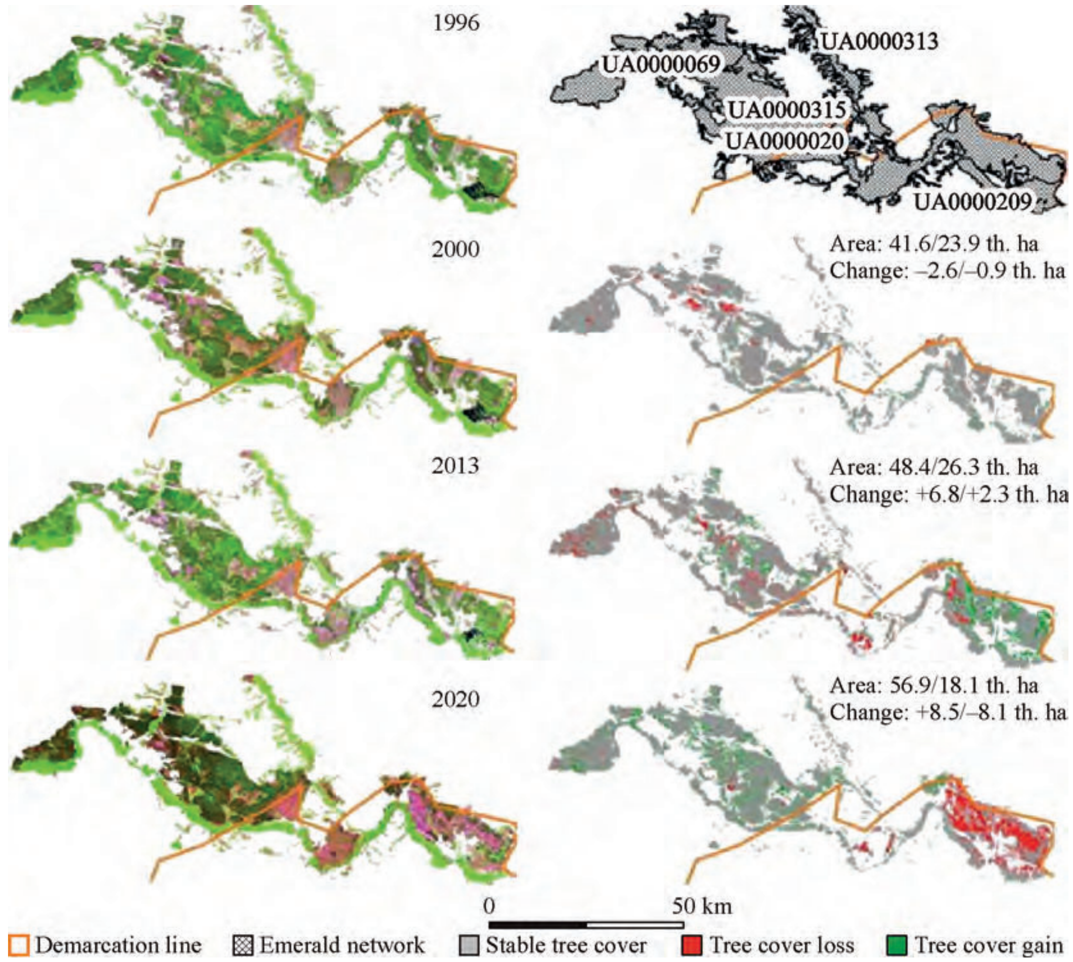

Fig. 8. Emerald Network sites established on the blanks of Siverskyi Donets river in Luhansk region. The map represents Emerald Network sites with IDs UA0000069, UA0000315, UA0000209, UA0000078, and the southern portion of UA000031377. The left images show Landsat images for 1996 to 2013 and Sentinel-2 images for 2020 in false color with short wave infrared 1 (–1.6 ^m), near-infrared (~0.8 ^m), and blue (~0.4 ^m) band combinations. The right images show the stable, gained, and lost tree cover for respective years and time periods. Areas and changes represent tree cover changes and net gains for territories under Ukraine and Russia's control, respectively

impact of the territory's separation on the environment by comparing forest area changes in territories under Ukrainian and Russian control. Gathering ground-referenced data in active conflict zones is impossible because of the high risks to security. Consequently, we employed remote sensing-based approaches, commonly used for assessing areas affected by warfare, to analyze changes in land cover and land use before, during, and after the conflict. We chose 1996 to 2020 as a research time period for the analysis because during these years Ukraine joined The Bern Convention, and the planned final year for Emerald Network establishment (excluding time after the catastrophic wildfire). This time period is further divided into three parts. The first (from 1996 to 2000) shows the trend before the creation of the Emerald Network. The second (from 2000 to 2013) shows the progress of the Emerald Network establishment before the conflict. The third (from 2013 to 2020) shows the progress of conservation after the beginning of the conflict. After the end of the Russian-Ukrainian war, the establishment of a stable demarcation line, and ecosystem's restoration process beginning, the methodology presented in this article can be extended to other regions of Ukraine for the post-war ecosystem conservation damage assessment.

We carried out a land-cover change assessment with the use of generated maps of the Luhansk region for 1996, 2000, 2013, and 2020. The accuracy values of tree cover maps in terms of F1 score (which is the harmonic mean of the user's accuracy and producer's accuracy68) were 0.9, 0.9, 0.84, and 0.88, correspondingly.

Between 1996 and 2000, the annual deforestation rate on the territories under Ukrainian control was −0.86 ± ± 0.22 th. ha per year or overall –3.42 ± 0.86 th. ha. A similar rate was observed in territories taken under Russian control after 2014 at an annual rate of –0.28 ± 0.1 th. ha per year or overall −1.1 ± 0.4 th. ha. Since 2000 Ukrainian government considered the creation of Emerald Network sites as a priority for the short- and long-term environmental-protection strategies. After work began on establishing Emerald Network sites and implementing EU sustainable development policies, changes in trends on both parts of the Emerald Network are evident. Between 2000 and 2013, annual reforestation rates in territories under Ukraine control were +0.67 ± 0.09 th. ha per year with +8.7 ± 1.2 th. ha total forest area growth. At the same time, territories that were to be under Russian control had an annual rate of +0.19 ± 0.06 th. ha per year and total +2.48 ± 0.79 th. ha growth. The military conflict in 2014, and the subsequent segmentation of territory on the occupied and non-occupied by demarcation line, changed trend's patterns during 2013—2020. During this time period, we found that territories that remained under Ukraine's control kept in place reforestation and conservation processes with +1.19 ± 0.18 th. ha per year annual rate and total area in an increase of +8.3 ± 1.25 th. ha. However, territories that were taken by the Russian control experienced rapid deforestation of –1.23 ± 0.15 th. ha per year annual rate and –8.6 ± ± 1 th. ha total forest area loss. Results (Supplementary Tables 2 and 3) indicate that territories remained under Ukraine's control even under the conditions of military conflict with increased vulnerability and consequent ecological problems in the region continued progression of conservation while territories under Russian control lost 20 years of sustainable development progress with 25% of forest loss (compared the 2013 estimates).

The majority of forest area in the Luhansk region is concentrated in the floodplains of the Siverskyi Donets River site (Fig. 8) and was divided into two parts by a demarcation line. Both parts have the same ecological communities of flora and fauna and are equally vulnerable to ecological problems due to post-military action damage. Before the conflict in 2014, this area was entirely under Ukrainian government control and not segmented; this is reflected by the uniform and consistent land-cover change trends before the war. However, after the partial separation of the region, we observed severe deforestation. Between 2013 and 2020, Ukraine-controlled territories gained 18% of forest area, while Russia controlled lost 31%.

Our analysis indicates that Ukraine achieved a total reforestation area of 11.17 ± 1.45 th. ha before the beginning of the conflict and 17 ± 1.74 th. ha from 2000 to 2020 on the Ukraine-controlled territories. At the same time, deforestation rates of territories under Russian control with similar bio-physical characteristics and the same war-related vulnerability factors indicate that the separation of ecosystems from environmental protection institutions and policies through the occupation of territory led to dramatic degradation of the environment and loss of ecosystem sustainability.

European forest types mapping using high-fidelity satellite data

Accurate and up-to-date forest type maps are crucial for effective monitoring and management of forest ecosystems across Europe. However, the availability of up to date high-resolution forest type maps has been limited. This study introduces an innovative semi-supervised approach for mapping European forest types by harnessing the power of high-resolution Sentinel-1 and Sentinel-2 satellite data from the Copernicus program. The novelty of the approach lies in the integration of various data sources for training dataset creation and the utilization of the Random Forest classifier on the Google Earth Engine cloud computing platform. This innovative combination enables efficient processing and classification of vast amounts of satellite imagery for large-scale forest type mapping. In particular, the LUCAS Copernicus 2018 and 2022 datasets were employed for training and validation, ensuring the robustness of the classification model. The resulting forest type map for 2022 has a fine spatial resolution of 10 meters and distinguishes between three key classes: broadleaved, coniferous, and mixed forests. Accuracy assessment using independent validation data demonstrated the reliability of the proposed approach, yielding an impressive overall accuracy of 93%. Comparative analysis with existing forest products revealed both consistencies and differences, underscoring the dynamic nature of forest ecosystems. The generated map fills a gap in up to date geospatial information on European forest types, empowering informed decision-making in forest management, conservation efforts, and environmental impact assessment. This study demonstrates the potential of synergizing cutting-edge remote sensing, cloud computing, and machine learning technologies to tackle complex environmental challenges at a continental scale, paving the way for future advancements in forest monitoring and management.

For forest type classification we have used 12-day mean composites of SAR Sentinel-1 satellite data with VV, VH bands with 10-meters spatial resolution and Sentinel-2 data with preprocessing Level-2A and a spatial resolution of 10 meters are employed in Google Earth Engine cloud platform [14, 15]. The revisit time of Sentinel-2 is every 5 days; however, due to significant cloud cover, three composites are generated and used.

For training and testing the creation of forest type maps for Europe, the LUCAS Copernicus 2018 open dataset serves as the primary resource. Despite being based on 2018 data, this dataset remains suitable for forest type classification due to the relatively slow change in forest types over time. A five-year span is not considered extensive for a land cover type like forests. To update this dataset for 2022, the global land cover data from WorldCover 2021 was utilized. Samples that exhibited a change in class between 2018 and 2021 were subsequently excluded from consideration. The great advantage of LUCAS Copernicus 2018 data set is that for each sample there were 5 photos that confirm the correctness of the class that is entered for this sample. Fig. 9 illustrates the geospatial distribution of the resulting dataset for three types of forests (broadleaved, coniferous, and mixed). To train the model and validate the resulting product, the dataset was divided into an 80:20 ratio within each distinct group of countries.

The prepared stack of satellite Sentinel-1 and Sentinel-2 composites together with prepared pre-filtered LUCAS

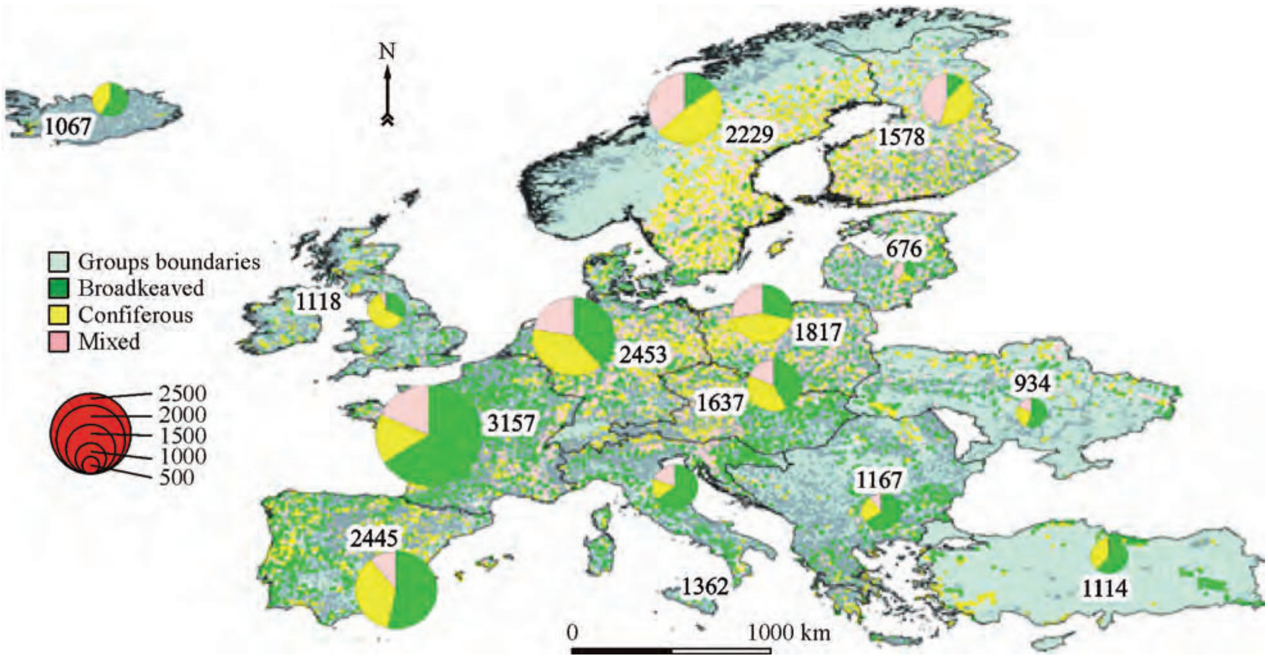

Fig. 9. The geospatial distribution of the prepared data set for 3 types of forests (broadleaved, coniferous and mixed) by selected groups

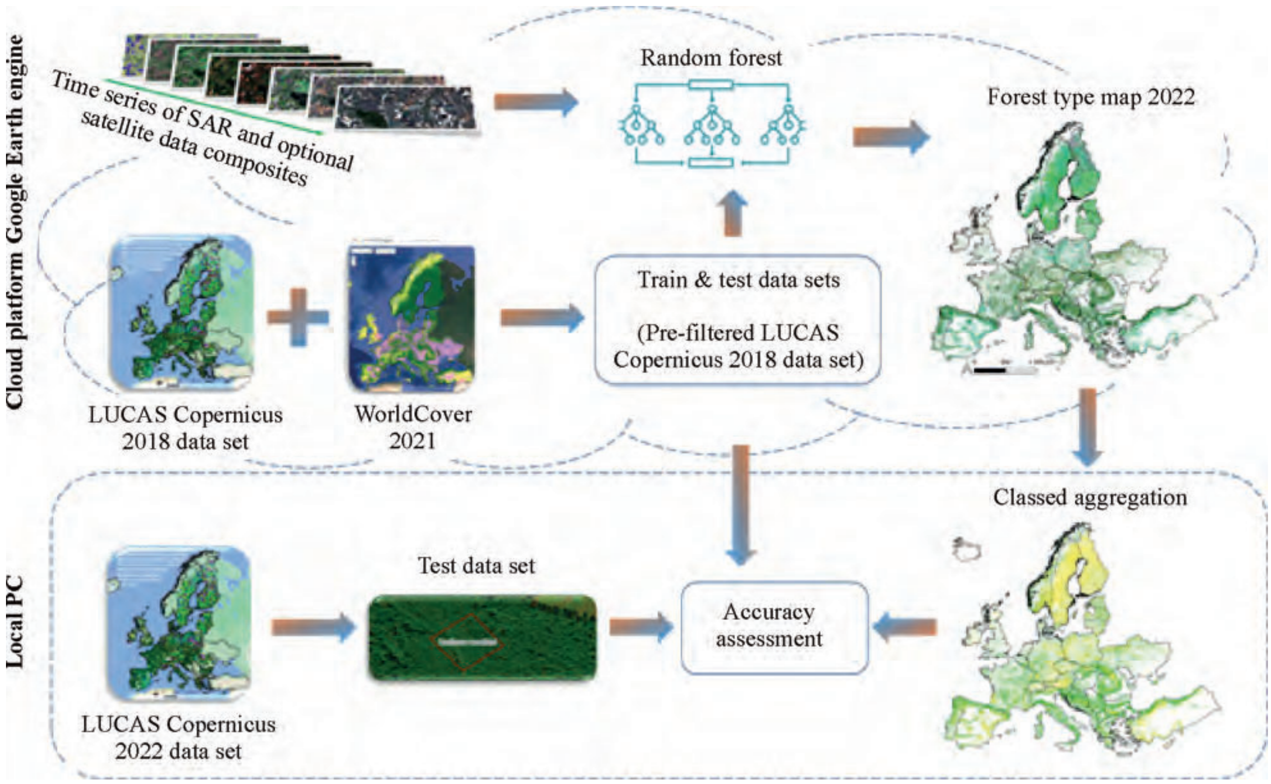

Fig. 10. Workflow of forest type map creation

Copernicus 2018 train data were used as input data for forest type classification. All data (satellite and train data set) is contained in cloud and we don't need extra resource to train the classifier. For each separate group of countries, we trained different Random Forest models due to GEE capacity with 100 number of trees. Leveraging the cloud platform Google Earth Engine facilitates seamless scalability and utilization of the model across extensive areas, particularly throughout Europe, as demonstrated by previous studies [7, 15]. The developed methodology for obtaining a classification map of forest types for Europe [8, 16] is schematically presented in the Fig. 10.

The main outcome of this study is the forest type classification map for the year 2022 covering the European territory, featuring a spatial resolution of 10 meters. The overall accuracy of created map is more than 90%. The resulting map includes 3 forest type classes (broadleaved, coniferous and mixed) and available for visualization by the link https://ee-swiftt.projects.earthengine.app/view/foresttype [9].

Conclusions

This article has demonstrated the immense potential of integrating advanced remote sensing data, computational machine learning techniques, and cloud computing platforms for addressing complex challenges in forest ecosystem monitoring and management. The developed approaches have yielded promising results across three main areas of investigation.

Firstly, the proposed automated feature engineering framework based on genetic algorithms has showcased remarkable performance in identifying informative features for semantic segmentation of damaged forest areas from satellite imagery. By numerically evaluating feature informativeness and independence, and leveraging a simplified representation of vegetation indices, this method has proven effective in optimizing feature sets for accurate segmentation. The elimination of manual feature selection and model training processes represents a significant advancement, enabling efficient analysis of vast satellite data repositories with minimal labeled data requirements.

Secondly, the intellectual analysis of forest cover change dynamics in conflict zones has provided insights into the detrimental impact of militarized occupation on ecosystem sustainability. Through the analysis of time-series satellite imagery, this study has quantitatively demonstrated the stark contrast in deforestation rates between areas under Ukrainian control, where conservation efforts were maintained, and those under Russian occupation, which experienced rapid and severe deforestation. These findings underscore the critical importance of environmental protection policies and institutions in preserving forest ecosystems, even amidst challenging circumstances such as armed conflicts.

Thirdly, the innovative semi-automated approach for mapping European forest types has yielded highly accurate and up-to-date geospatial information on a continental scale. By harnessing the power of high-resolution Sentinel-1 and Sentinel-2 satellite data, in conjunction with the Random Forest classifier and the Google Earth Engine cloud computing platform, this methodology has overcome the limitations of traditional mapping techniques. The resulting 10-meter resolution forest type map for 2022, distinguishing broadleaved, coniferous, and mixed forests, with an overall accuracy of 93%, represents a significant contribution to informed decision-making in forest management and conservation efforts across Europe.

The successful integration of cutting-edge technologies, including remote sensing, machine learning, and cloud computing, has opened new frontiers in the field of forest monitoring and management. By leveraging the synergies between these domains, researchers and practitioners can overcome the challenges posed by the vast scales and complexities of forest ecosystems, enabling more comprehensive, accurate, and timely assessments.

Future research endeavors should focus on further refining and enhancing these methodologies, exploring the incorporation of additional data sources such as ground-based observations and climate models, and expanding their applications to diverse forest ecosystems worldwide. Collaborative efforts between researchers, policymakers, and stakeholders will be crucial in translating these technological advancements into tangible impacts on sustainable forest management, biodiversity conservation, and climate change mitigation efforts.

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