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Monitoring tree mortality in Ukrainian *Pinus sylvestris* L. forests using remote sensing data from earth observing satellites

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Abstract This article considers the application of remote sensing data to solve the problems of forestry in the Polissia zone (Ukraine). The satellite remote sensing was shown to be applicable to monitoring the damage caused by diseases and pests to forest resources and to assessing the effects of fires. During the research, a detailed analysis and optimization of the information content of Sentinel-2 long-term data sets was performed to detect changes in the forest cover of Polissia, affected by pests and damaged by fires. The following classification algorithms were used for automated decryption: the maximum likelihood method; cluster classification without training; Principal Component Analysis (PCA); Random Forest classification. The results of this study indicate the high potential of Sentinel-2 data for application in applied problems of forestry and vegetation analysis, despite the decametric spatial resolution. Our proposed workflow has achieved an overall classification accuracy of 90 % for the Polissia region, indicating its reliability and potential for scaling to a higher level, and the proposed forecast model is stationary and does not depend on time parameters. To improve the classification results, testing of different combinations of bands emphasized the importance of Band 8 in combination with red edge bands, as well as other bands with a resolution of 10 m for summer scenes. The red margin shows clearly visible differences in the spectral profiles, but bands with a higher resolution of 10 m were crucial for good results.

Keywords: forest fires, pine, deforestation, maximum likelihood method.

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Introduction

Three decades have passed since the launch of the first international satellite sensor program to monitor the Earth's resources (Boyd & Danson 2005). During this period, forest resources were under increasing pressure, so their management and use need to be supported by information about their properties at many levels. Satellite remote sensing has been used to estimate forest resources since the launch of the first satellite Earth resource sensor

(ERTS) in 1972. Since then, methods have been developed for spectral analysis of forests and mapping on a regional scale of data on deforestation, age, species composition and forest types, as well as their ecological status (Tomppo et al. 2008, Vega Isuhuaylas et al. 2018, Valbuena et al. 2016, Wessel et al. 2018). The use of remote sensing in the assessment of forest resources provides three levels of information; namely, the spatial scale of forest cover, which can be used to assess the spatial dynamics of forest cover; forest type and biophysical and biochemical properties of forests. The assessment of the information about forests opens up opportunities for comprehensive monitoring of forest resources and performance of a range of functions that will raise the level of ecological safety of forest ecosystems to a higher level.

In many countries, high-resolution remote sensing of the Earth is now used to classify landscapes affected by deforestation, with land and forest cover maps used as baseline data to build accurate data sets, and digital maps and the database of coniferous species are used as reference data (Lee et al. 2020).

This article provides an overview of how to use satellite remote sensing today for forestry applications. Evidence from similar studies in other countries highlights the future potential of satellite remote sensing for monitoring forest resources in Ukraine. Forest fires, deforestation and damage to forests by pests and diseases should be singled out among the urgent problems of forestry. This will be considered in the study.

Fire risk simulations in the expected climate change scenario indicate that in a relatively short period of the next decades, the destructiveness of forest fires will increase (Knorr et al. 2016, Lozano et al. 2017). Due to the same reasons, the indicators of forest damage by pests and diseases, which lead to mass mortality of *Pinus sylvestris* L. plantations in Polissia of Ukraine, are quite unpredictable at the moment. Existing management strategies, which include preparedness and early warning, cannot be generalized due to the multidirectional and multidimensional effects of environmental hazards in different plant zones and ecosystems and under different cultural, social and economic factors (Scholze et al. 2006). However, unlike most geological and hydrometeorological hazards included into the International Decade of Natural Disaster Reduction (IDNDR) Early Warning Program (IDNDR), in most cases, forest fires and the spread of diseases and pests are natural hazards, which can be predicted, controlled and, in many cases, prevented (UN Global Assessment Report on Disaster Risk Reduction - GAR, 2019). Early warning systems are important components of forest protection management systems.

Early prevention of fires and the risk of air pollution may include local indicators, such as local fire forecasts and assessment of vegetation dryness. However, advanced technologies that rely on remote sensing data, weather forecasting and international communication systems (such as the Internet) are now also available for remote locations.

Materials and Methods

In this study, we integrated multi-sensor remote sensing to determine the mortality of disease-caused trees in a forest area of 41,828 ha from 2017 to 2019. We chose the sudden mortality of the *Pinus sylvestris* L., as it is the main forest-forming species of the region, and also for the reason that in recent years the spread of pests (especially pine bark beetle - *Blastophagus piniperda* L.) has become extraordinary. During the research, a detailed analysis and optimization of the information content of long-term data sets Sentinel-2 was performed to detect changes in the forest cover of Polissia, affected by pests and damaged by fires. Forest plots of Narodychi Specialized Forestry Enterprize of Zhytomyr region (Ukraine) were selected for testing the method. The analysis of the current situation of Narodychi Specialized Forestry Enterprize showed that in general at the beginning of 2020 the centers of mortality of *Pinus sylvestris* L. plantations were found on an area of 1173 ha, with the area of plantations with single cases of mortality – 32 ha, group cases of mortality – 306 ha and forest stands ones – 1116 ha. According to the statistics of the this Enterprize, 1065 ha of pine stands are affected by *Blastophagus piniperda* L.

Images of the forest area of three different years (2017, 2018 and 2019) were calibrated by automatically decoding the satellite images.

State enterprise "Narodychi specialized forestry" is subordinated to the Zhytomyr Regional Division of Forestry and hunting, which in turn, is the territorial governing body of the State Agency of Forest Resources of Ukraine (the central state executive body of Ukraine for forestry and hunting). The Narodychi SF is located in the north-eastern part of the Narodytsky and Malynsky administrative districts of the Zhytomyr region (Figure 1).

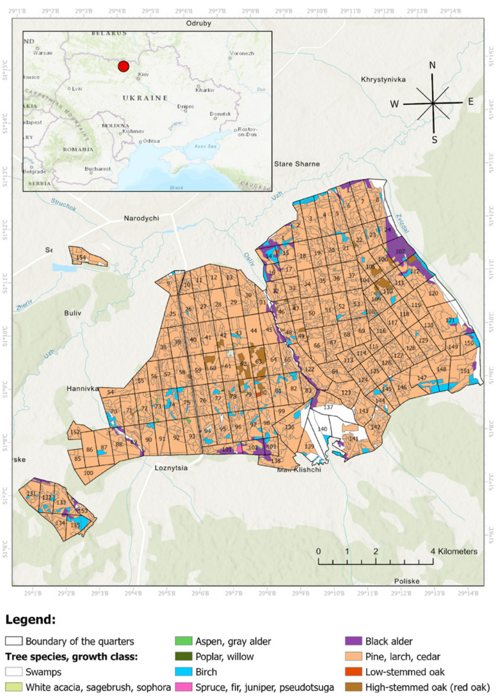

Figure 1 The study area.

The study area borders with the forests of the agroindustrial complex as well as with agricultural land. However, a lot of radioactive waste was accumulated on these lands after the Chernobyl accident, so they cannot be used for their intended purpose. According to the forest vegetation zoning, the territory of the forestry belongs to the zone of mixed coniferous-deciduous forests of Central Polissia.

The total area of the forestry enterprise is 65200 ha, including 56431 ha covered with forest vegetation. Furthermore, there are 5809 ha of the area without forest vegetation cover and 2960 ha of non-forest lands.

The climate of the area is temperate continental and is characterized by moderate mild winters, warm summers with high rainfall. In general, the climate of this forest area is favorable for the successful growth of tree and shrub species such as *Pinus sylvestris* L., *Picea abies* (L.) Karst., *Betula pendula* Roth., *Alnus glutinosa* (L.) Gaerth., *Sambucus nigra* L., *Corylus avellana* L. and others. Therefore, the enterprise has the plantations of the main forest-forming species of high quality.

Sod-podzolic soils are the most widespread in SE "Narodychi SF" (90% of forested lands). Most of the enterprise's forests belong to the fourth forests category (operational forests) – 52.9%, protective forests of the first group are

Table 1 Dynamics of distribution of forest lands by their categories.

Indicators	According to the forest inventory statistics	
	as at 01.01.2009	as at 01.01.2017
The total area of forest lands, ha	55495.0	64410.8
of which: Forest lands	52561.0	61495.9
including: - covered with forest vegetation	48965.2	56148.4
- - non-closed forest plantations	1449.1	1812.0
- forest nurseries	2.1	7.9
- burnt forest	61.2	130.3
- cut down area	378.7	1499.8
- meadows, bio-meadows, wastelands	689.8	799.6
- forest paths, clearings, ditches	994.1	1077.1
Non-forest lands:	2934.0	2914.9
of which: -agricultural land	7.4	14.2
- water bodies	86.9	88.3
- swamps	1132.6	1283.5
- estates, buildings	31.7	31.8
- tracks	36.8	44.0
- other non-forest lands	1638.6	1453.1

Note: The area of forest lands increased by 17%, the area of non-forest lands has barely changed.

31%, lanes along roads and railways are 10%. The most common species is Scots pine (*P. sylvestris*) (88%). In wet locations the dominant position is occupied by Black alder (*A. glutinosa*). All plantations in wet places have an admixture of Hanging birch (*B. pendula*).

The dynamics of the enterprise forest fund in comparison with the forest inventory of 2009 are given in tables 1-3.

Table 2 Monitoring the dynamics of the species composition of stands.

Dominant tree species	Forest inventory at 01.01.2017	
	area, ha	%
Pinus sylvestris **L.**	48873.7	86.7%
Picea abies (L.) H.Karst.	26.9	0.0%
Larix decidua Mill.	0.8	0.0%
Conifers together	48901.4	86.7%
Quercus robur L.	768.4	1.4%
Carpinus betulus L.	34.5	0.1%
Fraxinus excelsior L.	49.5	0.1%
Acer platanoides L.	0.2	0.0%
Robinia pseudoacacia L.	1.1	0.0%
Hardwoods together	853.7	1.5%
Betula pendula Roth	4549.3	8.1%
Populus tremula L.	243.4	0.4%
Alnus glutinosa (L.) Gaertn.	1850.4	3.3%
Tilia cordata Mill.	0.3	0.0%
Populus alba L.	1.4	0.0%
Deciduous together	6644.8	11.8%
Total	*56399.9*	*100.0%*

Table 3 Dynamics of other average inventory indicators.

Dominant tree species	Age, years	Quality class	Completeness (relative)	Total
Pinus sylvestris	61	1.7	0.75	228.78
Picea abies	53	1.1	0.83	0.17
Larix decidua	50	1.3	0.7	–
Quercus robur	66	2.5	0.74	2.08
Carpinus betulus	57	2.3	0.69	0.13
Fraxinus excelsior	63	1	0.73	0.22
Acer platanoides	31	1	0.71	–
Robinia pseudoacacia	53	1.7	0.58	–
Betula pendula	38	1.9	0.73	17.15
Populus tremula	56	1.6	0.75	1.16
Alnus glutinosa	50	1.9	0.72	7.49
Tilia cordata	58	1.0	0.70	–
Populus alba	54	4	0.61	–

Total: Total average stock change.

The data in the table above show that the average inventory indicators for the last audit period have not changed significantly.

According to the density of cesium 137 contamination, the territory of the specialized enterprise is divided as follows:

- up to 5 Ci/km^2 - 12,708 ha;
- 5,1-10 Ci//km^2 - 7,507 ha;
- 10,1-15 Ci//km^2 - 6,581 ha;
- 15,1-30 Ci//km^2 - 19,945 ha;
- 30,1-40 Ci//km^2 - 3,479 ha;
- 40,1-80 Ci//km^2 - 4,727 ha;
- > 80 Ci//km^2 - 325 ha.

The site was selected taking into account the data of route surveys and the study of forest management data of the respective forestry.

Materials from the Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) toolkits (Table 4), the Sentinel-2 MSI satellite sensor, were used to solve the problems of using GIS technologies for landscape safety using remote sensing data of the Earth's surface. The satellite information processing products used in this study are located on the Portal of the United States Geological Survey, in the Fire Information for Resource Management System (FIRMS). This method has already been used in our previous studies, for data processing in determining the electrical conductivity of the soil in Dniprovsko-Orilskyi Nature Reserve and biodiversity analysis of the Chernobyl Radiation and Ecological Biosphere Reserve, and also showed considerable informativeness (Zhukov et al. 2016, Fedonyuk et al. 2020, Skydan et al. 2021, Zymaroieva et al. 2021, Fedoniuk et al. 2021).

Table 4 Main characteristics of the spectral ranges of OLI and TIRS sensors, which are installed on the MSI sensor satellite Sentinel-2.

Spectral channel	Wave length (microns)	Resolution (m)
	Sentinel-2	
MultiSpectral Instrument (MSI)		
B1 (blue)	0.43–0.45	60
B2 (blue)	0.46–0.52	10
B3 (green)	0.54–0.58	10
B4 (red)	0.65–0.68	10
B5 (red edge)	0.70–0.71	20
B6 (red edge)	0.73–0.75	20
B7 (red edge)	0.77–0.79	20
B8 (NIR)	0.78–0.90	10
B8a (NIR)	0.86–0.88	20
B9 (water vapor)	0.93–0.95	60
B11 (SWIR1)	1.57–1.66	20
B12 (SWRIR2)	2.10–2.28	20
B10 (cirrus)	1.37–1.39	60

To monitor the safety of landscapes, we used the indices, which were derived from the spectral channels of sensors, which are installed on the satellites Landsat-8 or Sentinel-2 (ratio of spectral bands) (Kunah & Papka 2016). Geometric rectification was accompanied by procedures for normalization and correction of the atmosphere. Normalization consisted of statistical regression over time based on spatially clearly defined and spectrally stable features of the landscape, covering the entire range of reflection. The adjustment mechanism used a dark object subtraction technique that includes published water reflection values (Ding et al. 2015). The relationship between digital data and forest cover has been maximized and interpretation improved by converting band-specific reflectance values into vegetation indicators. Plant bitemporal indices for each time interval (annually for three years) were subjected to two algorithms for detecting changes, standardized differentiation and selective analysis of the main components.

The optimal choice of features was based on statistical indicators of differences. The criterion for selecting homogeneous subgroups of spatial objects was statistical homogeneity of spectral characteristics, which is confirmed by means of ANOVA. The following classification algorithms were used for automated decryption. Initially, the images were processed automatically using the maximum likelihood method. In fact, this is a task recognition where, based on the shade of the color spectrum of the sample, the system assigns a new object to one or another category. Next, the data groups were subjected to cluster classification. Next, the formed cluster groups were analyzed for the reliability of the data obtained: Principal Component Analysis (PCA) and Random Forest classification. These methods were tested on images with different combinations of channels. By selection, it was determined that the application of the maximum likelihood method with the synthesis of channels 2/3/4/8 for multi-time data sets Sentinel-2 is the most accurate and informative in detecting areas of damage by *Blastophagus piniperda* L., and spectral channels 12/8a/4 to detect burns and fires.

Results

Recently, forest ecosystems have been increasingly affected by a variety of factors, including climate change, infectious diseases, and new pest species, leading to the formation of large areas of withering trees in northern Ukraine. In recent years, this problem has grown significantly, and illegal deforestation has begun, which has been repeated more often and on a more serious scale. This led to the destruction of large areas of forests. Mortality of trees can be monitored by remote sensing, although it is more difficult to differentiate the causes, as they can be diseases, as well as forest fires and droughts.

In the research, Sentinel-2 long-term data sets were obtained to detect changes in the forest cover of Polissia that have signs of mortality. Images of the forest area of three different years (2017, 2018 and 2019) were calibrated by automatically decoding the satellite images (Fig. 2). Affected by trunk pests, trees are characterized by a matte shade of the crown and needle shedding, which is easily identified using remote sensing methods (Senf et al. 2017). This allowed to determine the area affected: for 2017 it is 365 hectares of affected forest, which was 4.8 % of the total forest area, for 2018 – 441 hectares and 5.8 % and for 2019 – 634 hectares and 8.3 %, respectively.

The results show that the relationship between the spectral distribution of space imagery data and changes in forest canopy damage is quite clear and allows for operational use at the stage of stratification of forest cover changes to a more detailed assessment. For each image, a raster image was obtained with selected dried plantings, which were automatically converted into a vector format to facilitate the calculation of the affected areas in terms of quarters (Fig. 3).

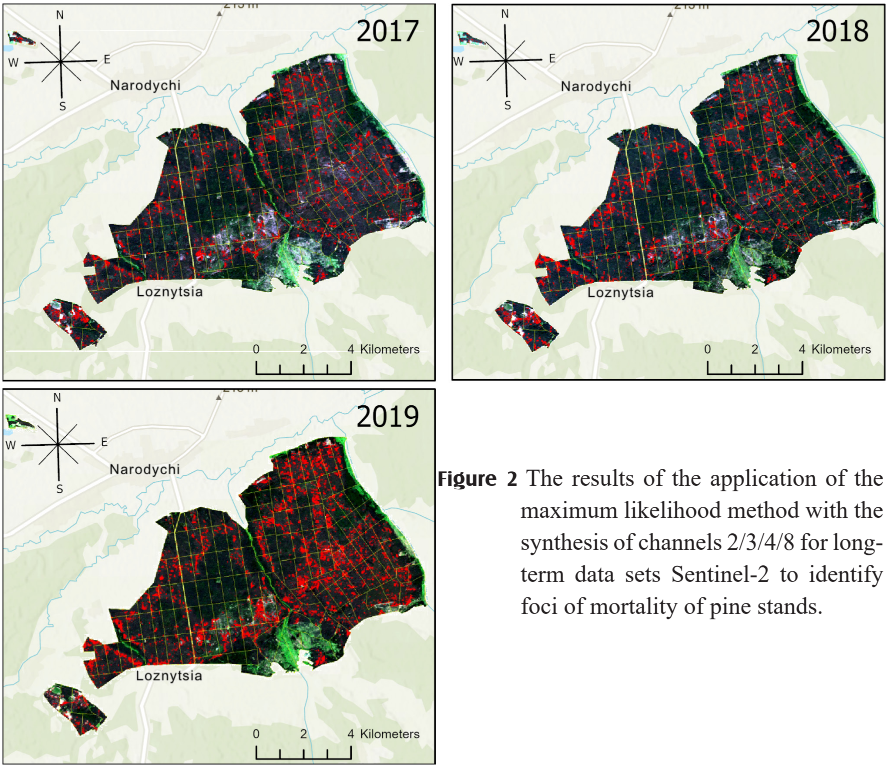

Figure 2 The results of the application of the maximum likelihood method with the synthesis of channels 2/3/4/8 for long-term data sets Sentinel-2 to identify foci of mortality of pine stands.

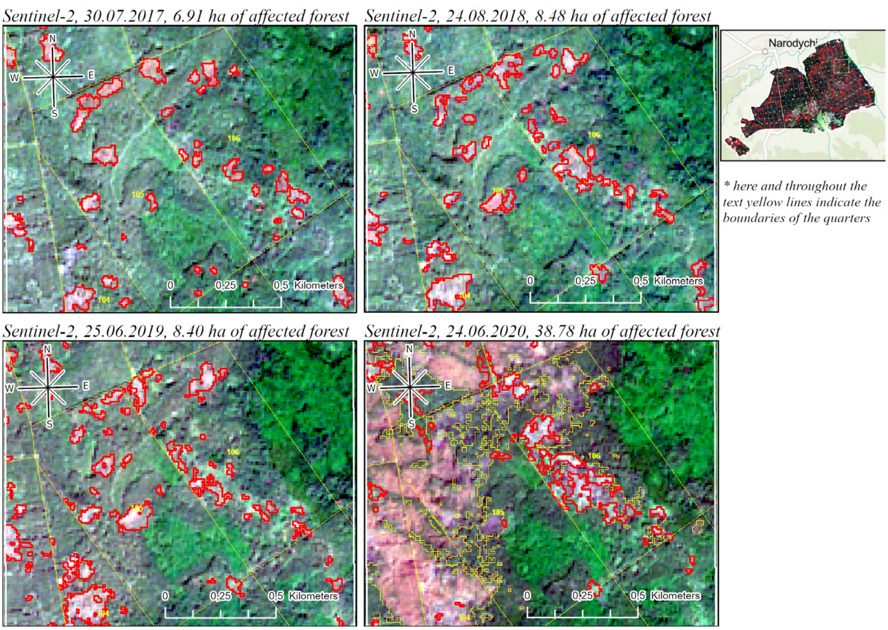

Figure 3 Examples of processing of Quarters 105 and 106 of Narodychi Specialized Forestry Enterprize when applying the maximum likelihood method.

For example, let's consider forest quarters 105 and 106. The data clearly allow to trace the centers of stand and group dying of *Pinus sylvestris* L. plantations.

We compared the obtained areas of *Blastophagus piniperda* L. with the actual field data on the lesions of the respective quarters of the economy using a general linear model that combines the possibilities of regression and analysis of variance. In this case, we combined continuous (Sentinel-2 data) and discrete predictors (years), which we mapped in pairs in the form of clear linear relationships for each year under study with correlation coefficients r = 0.93-0.94, which are statistically significant (Figure 3).

In addition, a statistical characterization of the obtained general linear model of the dependence of the observed values of the damage to *Pinus sylvestris* L. stands obtained on the basis of remote sensing of the Earth was performed. Given that the study took into account several predictors that are correlated and interdependent, it was determined that R_{adj} = 0.90, which indicates a high informativeness and effectiveness of the model (Table 5).

Table 5 General linear model of the dependence of the observed values on the values obtained on the basis of remote sensing data of the Earth ($R_{adj} = 0.90$, $F = 1335.9$, $p < 0.001$).

Influence	SS	Fr	MS	F-ratio	p-level
Intercept	0.01	1	0.01	0.02	0.88
Santinel-2	2000.10	1	2000.10	3540.54	<0.001
Year	0.09	2	0.04	0.08	0.92
Error	248.56	440	0.56	–	–

Note: SS: Sum of squares; Fr: Degrees of freedom; MS: The average sum of squares

Considering Table 6, the statistical significance of the model is also very high ($p < 0.001$). To construct predictive models, we used the observed regression and beta-regression coefficients of the general linear model, which allowed us to determine the criteria values. In particular, it should be noted that the predictor «year» is characterized by a low value, i.e. the model is stationary and does not depend on time parameters. The most important as a predictor are the values of long-term data sets Sentinel-2. Their values, standard error and confidence interval confirm the sufficiency of only this predictor for the formation of estimates and forecasts of mortality of *Pinus sylvestris* L. plantations without taking into account the values of other predictors.

The best kind of model of dependence of the observed values on the values received on the basis of data of remote sensing of the Earth is:

$Y = 0.84 \times X$,

where Y is the predicted value, X is the observed value.

Space images are subjected to similar manipulations to obtain information on the areas of fires. In Fig. 4

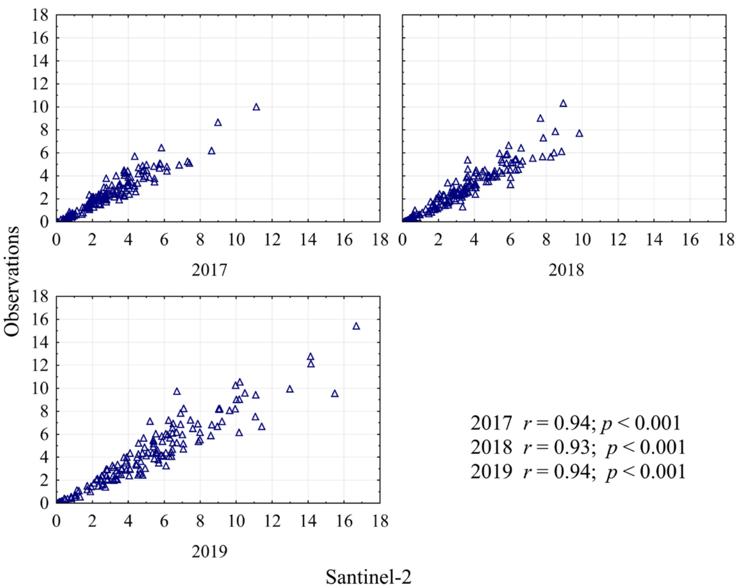

Figure 4 Scattering diagrams for the dependences of the observed values of the saturation area of pine stands, ha (ordinate axis) on the same values contained in the data of remote sensing data of the Earth, ha (abscissa axis) by years.

the maximum likelihood method with the synthesis of channels 12/8a/4 for multi-time data sets Sentinel-2 revealed the area of fires.

Table 6 Regression coefficients of the General linear model of dependence of the observed values on the values received on the basis of data of remote sensing of the Earth.

Influence	LF	*p*-level	Regression coefficients			Beta regression coefficients		
			coef±stderr	–95.0%	+95.0%	coef± stderr	–95.0%	+95.0%
Intercept	–	0.88	–0.01±0.07	–0.14	0.12	–	–	–
Santinel-2	–	0.00	0.84±0.01	0.82	0.87	0.95±0.02	0.92	0.98
Year	2017	0.88	0.01±0.05	–0.09	0.11	0.00±0.02	–0.03	0.04
Year	2018	0.79	0.01±0.05	–0.09	0.11	0.00±0.02	–0.03	0.04

Note: LF: The level of the factor; coef±std.err: coefficient ± standard error.

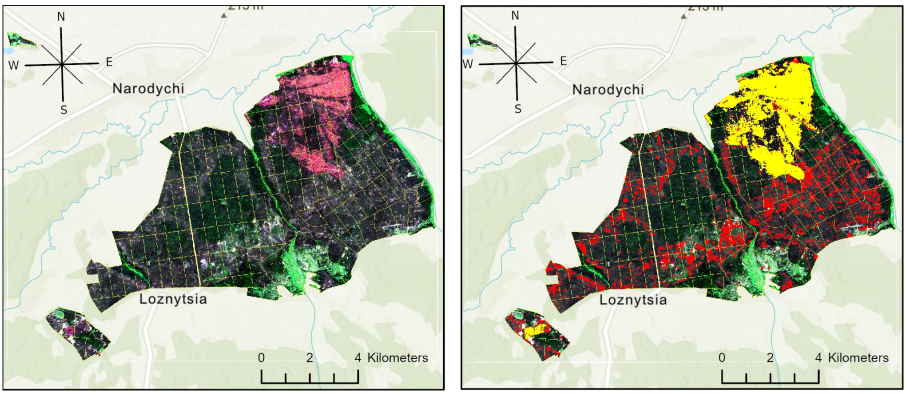

Figure 5 The results of the application of the maximum likelihood method with the synthesis of channels 12/8a/4 for multi-time data sets Sentinel-2 for fire detection (images before (left) and after (right) using of the method).

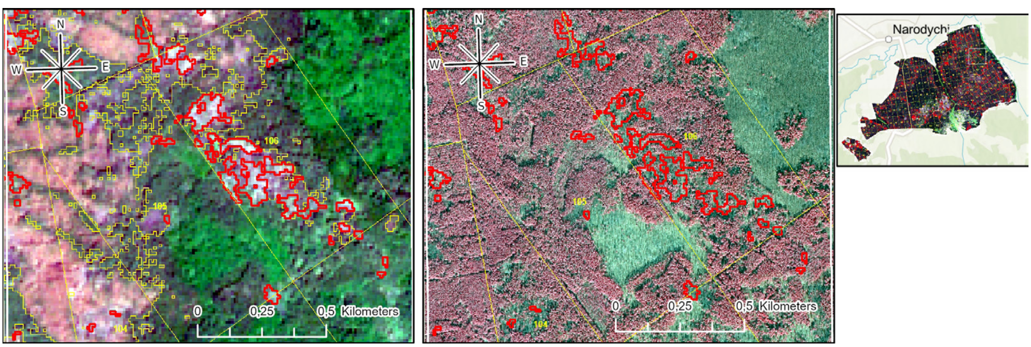

Figure 6 Sentinel-2 24.06.2020, after the fire, image from the spacecraft of high spatial resolution before the fire.

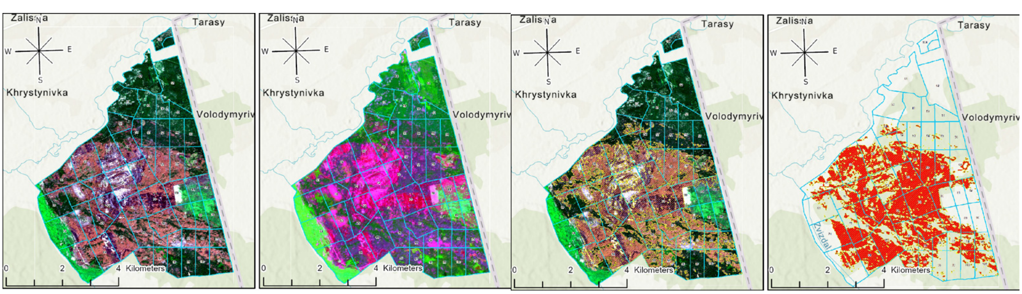

Figure 7 Vector layer of forest affected by fire (14.21 ha), Zaliske forestry, SE «Narodychi Specialized Forestry» (gradual classification by the maximum likelihood method).

For example, let's consider forest quarters 105 and 106 (Fig. 6), where in the spring of 2020 forest fires raged. High-resolution Sentinel-2A images use spectral channels (12/8a/4) to identify burns and fires, as well as with the help of Sentinel-Playground (https://apps.sentinel-hub.com/sentinel-playground/) from Sinergise (https://sinergise.com/en/solutions/sentinel-hub) you can use a combination of SWIR and NIR Sentinel-2 or Landsat bands, which allow you to make accurate maps of burned areas.

The SWIR band is sensitive to water content in soil and vegetation, while the NIR band is sensitive to vegetation (photosynthetic activity). In addition, the radiance measured by the space sensor at SWIR wave lengths increases if the surface is very hot (Fig. 7). As a result, a simple color composite of SWIR / NIR / Red bands gives clear outlines of fires and can highlight current areas of fire if the smoke is not too opaque.

Discussion

Mortality has spread to 134 thousand hectares, or almost 6% of all *Pinus sylvestris* L. forests, which are subordinated to the enterprises of the State Agency of Forest Resources of Ukraine. The largest centers of mortality are observed in the northern regions of Ukraine (Volyn, Zhytomyr, Kyiv, Chernihiv, Kharkiv, and Poltava). Plantations located in the Polissia and Forest-Steppe are the first to suffer.

It should be emphasized that this is not a problem of an individual economy, region, or Ukraine. Other European countries have faced such challenges. According to domestic scientists, due to climate change, the natural range of pine can shift from south to north to 300 km (Kravets & Pavlishchuk 2016). Rising temperatures, increasing the number of dry days, and other concomitant changes in the environment will lead to the emergence of such conditions to which *Pinus sylvestris* L. plantations do not have time to adapt.

First of all, it concerns artificial forests on the site of former agricultural lands. Such plantations are definitely less resistant to adverse natural conditions and require more care and attention from humans. The removal of the state from the protection and defense of such forests results in catastrophic environmental consequences - fires, the development of erosion processes, and then social and economic losses.

The results of this study indicate the high potential of Sentinel-2 data for application in applied problems of forestry and vegetation analysis, despite the decametric spatial resolution. Our proposed workflow has achieved an overall classification accuracy of 90 % for the Polissia region, indicating its reliability and potential for scaling to a higher level, and the proposed forecast model is stationary and does not depend on time parameters. To improve the classification results, testing of different combinations of bands emphasized the importance of Band 8 in combination with red edge bands, as well as other bands with a resolution of 10 m for summer scenes. The red part of the spectrum shows clearly visible differences in the spectral profiles, but bands with a higher resolution of 10 m were crucial for a good result. The lower spatial resolution (20 m) for the red edge area (Bands 5 – 7) somewhat reduces its ability to correctly classify vegetation, including tree vegetation. By selection, it was determined that the application of the maximum likelihood method with the synthesis of channels 2/3/4/8 for multi-time data sets Sentinel-2 is the most accurate and informative in detecting areas of deforestation and spectral channels 12/8a/4 – to detect burns and fires.

Conclusion

Recently, forest ecosystems have been increasingly affected by a variety of factors, including climate change, infectious diseases, and new pest species, leading to the formation of large areas of withering trees in northern Ukraine. In recent years, this problem has increased significantly, outbreaks of deforestation have occurred more frequently and more seriously, and have led to the destruction of large areas of trees.

Our research also shows that the mortality of trees can be monitored by remote sensing, although it is more difficult to differentiate the causes, as they can be diseases, as well as forest fires and droughts. In our research results, we present data to understand the spatial benefits of using the maximum likelihood method for the northern region of Ukraine and propose remote sensing approaches due to limited spatial and spectral resolution.

The findings show that the overall mapping accuracy ranges from 76% to 83%. We concluded that the proposed configuration is well suited for use in large areas with a similar forest structure and simplifies the workflow for applied forestry by providing the results for field validation and data collection. We have shown that Sentinel-2 data is a suitable, free alternative to commercial satellite data with a higher spatial resolution for classifying trees using machine learning algorithms.

References

Boyd D.S., & Danson F.M. 2005. Satellite remote sensing of forest resources: three decades of research development. *Progress in Physical Geography: Earth and Environment*, *29*(1), 1–26. https://doi.org/10.1191/0309133305pp432ra

Ding H., Shi J., Wang Y., & Wei L. 2015. An improved dark-object subtraction technique for atmospheric correction of Landsat 8. In *MIPPR 2015: Remote Sensing Image Processing, Geographic Information Systems, and Other Applications*, 9815, 128-135. https://doi.org/10.1117/12.2205567

Fedonyuk T.P., Galushchenko O.M., Melnichuk T.V., Zhukov O.V., Vishnevskiy D.O., Zymaroieva A.A., & Hurelia V.V. 2020. Prospects and main aspects of the GIS-technologies application for monitoring of biodiversity (on the example of the Chornobyl Radiation-Ecological Biosphere Reserve). *Space Science and Technology*, *26*(6). https://doi.org/10.15407/knit2020.06.075

Fedoniuk T., Borsuk O., Melnychuk T., Zymaroieva A., & Pazych V. 2021. Assessment of the consequences of forest fires in 2020 on the territory of the chornobyl radiation and ecological biosphere reserve. *Scientific Horizons, 24*(8), 26-36. https://doi.org/10.48077/scihor.24(8).2021.26-36

Isuhuaylas L.A.V., Hirata Y., Ventura Santos L.C., & Serrudo Torobeo N. 2018. Natural forest mapping in the Andes (Peru): A comparison of the performance of machine-learning algorithms. *Remote Sensing*, *10*(5), 782. https://doi.org/10.3390/rs10050782

Knorr W., Arneth A., & Jiang L. 2016. Demographic controls of future global fire risk. *Nature Climate Change*, *6*(8), 781-785. https://doi.org/10.1038/nclimate2999

Kravets P.V., & Pavlishchuk O.P. 2016. Lisova haluz Ukrainy v konteksti yevropeiskykh vymoh do zabezpechennia zakonnosti pokhodzhennia derevyny. *Naukovyi visnyk NLTU Ukrainy*, 26(8).

Kunah O.M., Papka O.S. 2016. Ecogeographical determinants of the ecological niche of the common milkweed (Asclepias syriaca) on the basis of indices of remote sensing of land images. Visnyk of Dnipropetrovsk University. *Biology, Ecology, 24*(1)**,** 78-86. https://doi.org/10.15421/011609

Lee S.H., Han K.J., Lee K., Lee K.J., Oh K.Y., & Lee M.J. 2020. Classification of landscape affected by deforestation using high-resolution remote sensing data and deep-learning techniques. *Remote Sensing*, *12*(20), 3372. https://doi.org/10.3390/rs12203372

Lozano O.M., Salis M., Ager A.A., Arca B., Alcasena F.J., Monteiro A.T., ... & Spano D. 2017. Assessing climate change impacts on wildfire exposure in Mediterranean areas. *Risk Analysis*, *37*(10), 1898-1916. https://doi.org/10.1111/risa.12739

Scholze M., Knorr W., Arnell N.W., & Prentice I.C. 2006. A climate-change risk analysis for world ecosystems. *Proceedings of the National Academy of Sciences*, *103*(35), 13116-13120. https://doi.org/10.1073/pnas.0601816103

Senf C., Seidl R., & Hostert P. 2017. Remote sensing of forest insect disturbances: Current state and future directions. *International Journal of Applied Earth Observation and Geoinformation*, *60*, 49-60. https://doi.org/10.1016/j.jag.2017.04.004

Skydan O.V., Fedoniuk T.P., Pyvovar P.V., Dankevych V.Y., & Dankevych Y.M. 2021. Landscape fire safety management: the experience of Ukraine and the EU. *News of the National Academy of Sciences of the Republic of Kazakhstan, Series of Geology and Technical Sciences,* 6(450), 125-132. https://doi.org/10.32014/2021.2518-170X.128

Tomppo E., Olsson H., Ståhl G., Nilsson M., Hagner O., & Katila M. 2008. Combining national forest inventory field plots and remote sensing data for forest databases. Remote Sensing of Environment, 112 (5), 1982-1999. https://doi.org/10.1016/j.rse.2007.03.032 .

UN, 2019. Global Assessment Report on Disaster Risk Reduction (GAR), 2019 https://gar.undrr.org/report-2019

USGS 2020. Geological Portal of the US Geological

Survey. Electronic resource – access mode as of March 26, 2020: http://earthexplorer.usgs.gov

Valbuena R., Maltamo M., & Packalen P. 2016. Classification of forest development stages from national low-density lidar datasets: a comparison of machine learning methods. *Revista de Teledetección*, (45), 15-25. https://doi.org/10.4995/raet.2016.4029

Wessel M., Brandmeier M., & Tiede D. 2018. Evaluation of different machine learning algorithms for scalable classification of tree types and tree species based on Sentinel-2 data. *Remote Sensing*, *10*(9), 1419. https://doi.org/10.3390/rs10091419

Zhukov O.V., Kunah O.M., Taran V.O., Lebedinska M.M. 2016. Spatial variability of soils electrical conductivity within arena of the river Dnepr valley (territory of the natural reserve «Dniprovsko-orilsky»). *Biological Bulletin of Bogdan Chmelnitskiy Melitopol State Pedagogical University. 6*(2), 129–157.

Zymaroieva A., Zhukov O., Fedoniuk T., Pinkina T., & Hurelia V. 2021. The relationship between landscape diversity and crops productivity: Landscape scale study. *Journal of Landscape Ecology (Czech Republic), 14*(1), 39-58. https://doi.org/10.2478/jlecol-2021-0003

https://apps.sentinel-hub.com/sentinel-playground/?source=S2L2A&lat=40.4&lng=-3.730000000000018&zoom=12&preset=1_TRUE_COLOR&layers=B01,B02,B03&maxcc=20&gain=1.0&gamma=1.0&time=2020-10-01%7C2021-04-21&atmFilter=&showDates=false

https://firms.modaps.eosdis.nasa.gov

https://sinergise.com/en/solutions/sentinel-hub

The United States Geological Survey https://www.usgs.gov