Forest Storm Damage Detection Using EO Data and Machine Learning

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Abstract: Forests are threatened by various harmful abiotic and biotic influences. Increased frequency of wind disturbances because of climate change represents the main source of damage in European forests. In a relatively short time, stormy winds can destroy large forest areas and thereby disrupt regular management. The main damage is fallen, broken, and permanently bent trees which usually occur together. These damages in the forest vary in intensity and scale, from complete damage on larger and smaller areas to group damage as well as damage to individual trees. Therefore, the effective detection and mapping of the described damages is extremely important for forest management. The thunderstorm which hit the continental Republic of Croatia in July 2023 caused enormous damage to forests in terms of area and intensity. Consequently, the aim was to use the example of this event to contribute methodologically to the assessment of the extent and intensity of damage using EO data and the appropriate machine learning algorithm. The manuscript investigates and presents the advantages and possibilities of detecting and mapping damage in the forest at three spatial scales (multi-scale assessments): state, regional and forest management unit, as well as at different degrees of damage. The presented methodology and obtained results provide useful information about the scale and intensity of damage for a wide range of users.

Keywords: forest damage; storm; earth observation; machine learning.

1 Introduction

Due to climate change, we are witnessing more and more frequent extreme weather events. In this sense, damage to forests from floods, ice, snow and wind is becoming more and more significant from a forest management perspective (Stanturf 2024). Of the abiotic factors, the most significant harmful effect is the wind (Gardiner et al. 2013, Kislov and Korznikov 2020). From the point of view of forest management, wind is significantly different from a storm. The basic characteristic of a storm or hurricane is a wind whose strength exceeds 8 Beaufort (> 17 m/s; > 60 km/h). Storm winds with movement faster than 8 Beaufort can cause great damage. In a short time, usually in a few minutes, they destroy large forest areas and cause major disruptions in management. Damages are threefold and usually occur together; these are windbreaks, fallen trees and permanently bent trees (Vajda 1974). To what extent the forest (structure) will be resistant to the force of the storm wind, depends on the condition of the habitat, vertical and horizontal structure, mixture, type of trees, age, health and other environmental conditions (Ulanova 2000, Dalponte et al. 2020).

In continental Croatia, storms that cause material damage most often occur in weather situations with the appearance of clouds of strong vertical development with stormy winds, a large amount of precipitation of a short duration, and sometimes hail (Bajić 2008). Just such a thunderstorm hit the continental part of the Republic of Croatia (RC) on July 19, 2023, and on its way from the west to the east of the country caused enormous material damage (Figure 1). The most violent gusts of wind up to 180 km/h (11th and 12th Beaufort scale, severe storm and hurricane) accompanied by extremely heavy rain were recorded in the eastern part of the country, where catastrophic damage to forests occurred.

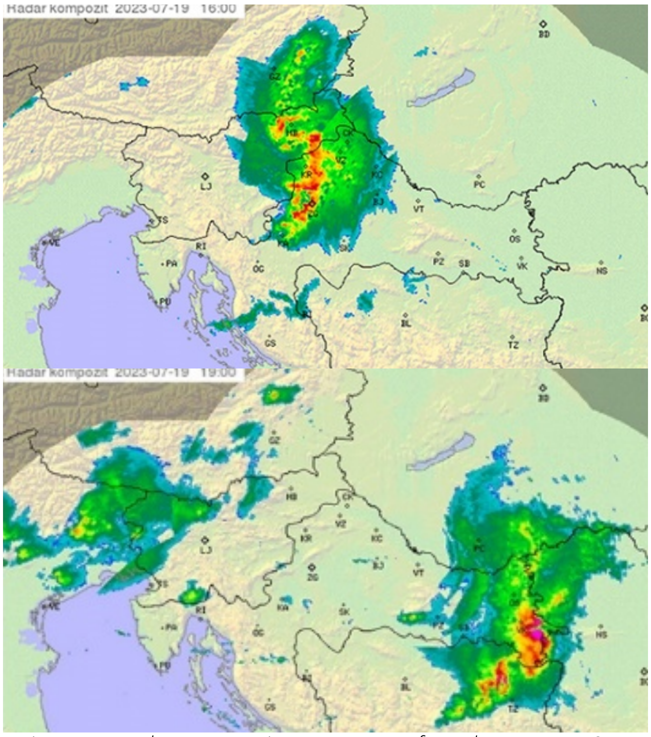

Figure 1. Radar composite: over part of northwestern RC on 07/19/2023. at 4 p.m. (top) and above over eastern RC at 7 p.m. (bottom). Source: https://meteo.hr/.

In the period of organized forest management, going back more than 250 years, no storm of this scale was recorded. In a relatively short time, the storm caused catastrophic damage to large forest areas and thus disrupted regular management. These damages in the forest are of different intensity and scale, from complete and partial damage on larger and smaller areas to damage on individual trees. From an economic point of view, the described damages represent a significant economic loss and in this case are of primary importance. Damage detection and assessment are critical and fundamental procedures in the process of forest management after a natural disaster (Chirici et al. 2018, Hamdi et al. 2019, Dalponte et al. 2020). Namely, damages must be quickly identified and mapped in order to ensure the choice of adequate procedures and dynamics in wood harvesting and forest restoration. In this sense, Earth Observation (EO) data are more than suitable, and to date various data sources and methodological approaches have been used for this purpose (Einzmann et al. 2017, Rüetschi et al. 2019, Dalponte et al. 2020, Pilaš et al. 2020).

In the RC, this issue has not been sufficiently investigated, nor has an official operational methodology for the application of EO in damage assessment been developed (Šimić et al. 2015, Pilaš et al. 2020). Therefore, this manuscript investigates the operational methodology of assessing the scale (hectares) and intensity (degrees) of damage in the forest, using available EO data and machine learning.

2 Materials and methodology

2.1 Research area

The research area refers to the continental part of the Republic of Croatia and includes forest complexes that were hit by the described storm (Figure 1). The assessment of forest damage was carried out at several levels: country, regional and local spatial scale.

2.2 Country scale assessment

The first step in the detection of damaged forest areas was the comparison of satellite imagery immediately before and after the event according to the "Change detection" principle. The aim of the analysis was the preliminary determination of possible forest damage, which should then be verified by field observation. For this purpose, Sentinel-2 (S-2), surface reflectance images with a small percentage of clouds from the period immediately before (July 1– July 18, 2023) and after (July 20 – August 1, 2023) the natural disaster were used. For each of the mentioned periods, cloud masking was first performed, and then mosaic imagery was created based on the median values of pixels for each band. On the obtained mosaic imagery, the Green Leaf Index (GLI) was calculated according to the formula:

$$\mathrm{GLI} = \frac{((\mathrm{GREEN} - \mathrm{RED}) + (\mathrm{GREEN} - \mathrm{BLUE}))}{((2 * \mathrm{GREEN}) + \mathrm{RED} + \mathrm{BLUE}))} \quad (1)$$

The GLI index used was aimed at detecting differences in vegetation cover changes based primarily on the color change that occurs due to the disruption of the forest stands when the reflection from the bare surface under the disturbed forest canopy comes to the fore. The GEE platform was used for this purpose.

2.3 Regional scale assessment -Forest administration unit

Country scale assessment (2.2) was used to identify areas of interest and represented the initial step towards a more detailed regional analysis of damage. On the country spatial scale, the most significant areas with damages in the continental part of the RC were singled out (Figure 2, Frames: 1-4). For more precise analysis and damage mapping, the area of the Spačva basin, which belongs to the Vinkovci forest administration and includes forest areas of about 70,000 hectares, was selected (Figure 2, Frame 1). For this purpose, a standard machine learning framework was used in which S-2 composite imagery before and after the windstorm served as predictor variables. On the S-2 data, random sampling was carried out on areas where damage was visible and on a part of areas without visible signs of windstorm. In this way, 1242 samples were collected, of which 848 were set aside for training and 394 for testing. To create the model, the Random Forest (RF) algorithm was used, which proved to be one of the most effective and reliable in supervised learning of remote sensing data (Maxwell et al. 2018, Whyte et al. 2018). Standard validation methods on the test set were used to evaluate the implemented binary classification (damage/no damage): test accuracy, confusion matrix, Kappa, Consumers accuracy and Producers accuracy (Olofsson 2014). The developed RF algorithm was then used to predict forest damage in the entire area of the forest administration unit.

2.4 Local scale assessment - Forest management unit

Mapping of damage at the local level, or at the level of the forest management unit, was done with the aim of providing operative support for forest management in the regeneration of damage from storm. For this purpose, five damage classes were defined, depending on the proportion of damaged trees within the stand (Classes: A: 0–10%; B: 10–20%; C: 20–50%; D: 50–80%; E: 80–100%). The set for training and validation, as a necessary segment of the machine learning pipeline, was created based on a visual assessment of damage at several points, from an updated very high-resolution image in Google Earth Pro, which was updated immediately after the windstorm and on which it was possible to recognize visible signs of damage to stands. A total of 84 points were selected, of which 71 were used for training and 13 for validation. To build a multiclass RF model, the same methodology and evaluation metrics were used as described in section 2.3, except that due to the small number of samples, the confusion matrix and class-oriented evaluation were not considered.

3 Results and Discussion

By analyzing satellite S-2 imagery based on the differences between the GLI index before and after the storm, areas with potential damage from storm were detected (Figure 2). After the preliminary selection of areas with potential damage, contact was made with the forestry operation, and in most cases the occurrence of forest damage in the detected areas was confirmed.

A further, more detailed assessment of damage from storm was made for the area of the Spačva basin in the eastern part of the RC (Figure 2, Frame 1), where the forest economic complexes were singled out. The verification of the RF model at 394 test points confirmed the very high reliability of the assessment, i.e. test accuracy of 0.96 (96%) and Kappa 0.93. The confusion matrix of binary classification confirmed that the RF model has a very small proportion of incorrectly estimated samples, i.e. only 3 false negatives and 11 false positives (Table 1).

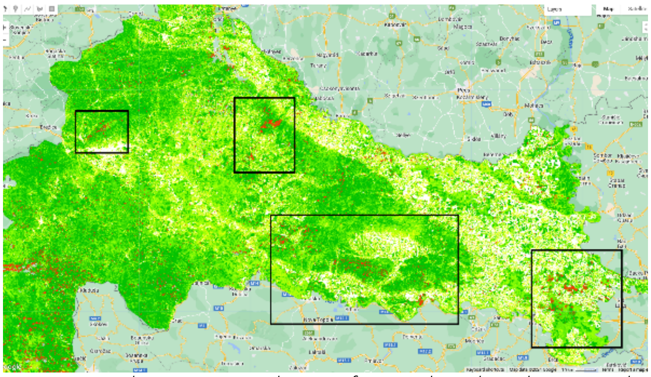

Figure 2. The continental part of RC with isolated potential locations with forest damage. Locations marked in red are highlighted on the recordings; (1) area of lowland forests - Spačva basin, (2) area of Slavonsko gorje (3) area of Bilogora and (4) Zagrebačka gora.

Producers' accuracy or a probability that a particular sample of the class is mapped as the same class in the classification map is 0.95 for positive category (Damage) and 0.98 for negative category (No damage). The consumer's accuracy, i.e. the accuracy of the map from the point of view of a map user is 0.98 for the positive category (Damage) and 0.94 for negative category (No damage). The achieved results are comparable to previous research (Einzmann et al. 2017, Hamdi 2019, Kislov and Korznikov 2020, Dalponte et al. 2020).

Table 1. Confusion matrix of binary classification with Random Forest algorithm.

		Actual values	
		Positive (Damage)	Negative (No damage)
Predicted values	Positive (Damage)	198	11
	Negative (No damage)	3	182

The developed RF was then used for the prediction and calculation of the forest areas affected by the storm for the entire Vinkovci forest administration (Figure 3 top). The total area of damaged forests was 11,929 hectares, which is about 15% of the total forest administration area of 77,199 hectares.

Validation of the created RF model for the multiclass classification of forest damages according to categories of forest cover damage (Classes: A: 0–10%; B: 10–20%; C: 20–50%; D: 50–80%; E: 80–100%) on the test data set confirmed the reliability of the assessment of 54% (total accuracy), in total for all classes and Kappa of 0.4. The above results are given preliminary. Although the achieved level of reliability of the assessment is significantly lower compared to binary classification, the results confirm the effectiveness of the mentioned approach with the need for additional improvement, especially in terms of increasing the number of sample points. This is in accordance with the suggestions of Maxwell et al. (2018) on the meaning of sample size and quality in relation to the applied algorithm.

Subsequent checks in the field have established that the created model quite well observes changes in the state of the forest cover and degrees of damage, and as such is justified for operational use, which can significantly simplify and speed up work in the field related to damage analysis and planning of silvicultural operations. For this reason, a prediction of forest damage classes was made for the selected area (Figure 3 bottom) and put into operational use (Mergin maps).

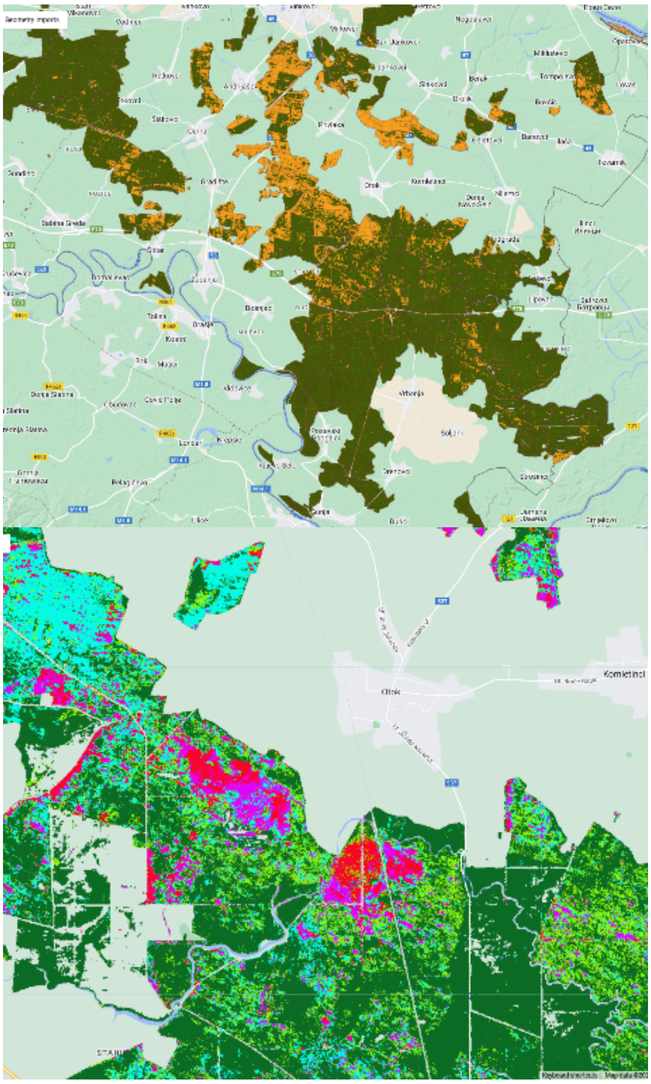

Figure 3. Prediction map of storm damage (brown color) in the Vinkovci forest administration area (top) and prediction of forest damage levels based on Sentinel-2 images and the RF model (bottom).

4 Conclusions

Forests are increasingly affected by adverse weather conditions. The storm from July 2023 is the last event with catastrophic consequences for the forests of continental of the RC. Therefore, the aim of this manuscript was to use the example of the described event to provide a methodological contribution to the assessment and mapping of the extent and intensity of damage using EO data. For this purpose, three spatial scale assessments and mapping of damage in forests are presented. In the first country scale assessment, potential areas of application of S-2 data and change detection approach were detected. In the second, regional scale assessment, more detailed and accurate damage mapping was carried out. In the isolated area (eastern part of the RC), the analysis of forest damage using the RF algorithm and the multiband S-2 predictor before and after the windstorm, showed that using the mentioned approach it is possible to carry out very precise and reliable mapping of damaged forest areas. Damage mapping at the economic unit level (forest management unit) was carried out with the aim of providing support for operational works. Despite the slightly lower accuracy (primarily due to the small sample), the field check found that the created map gives a good and very realistic assessment of the five levels of damage. Therefore, this damage map was added as a layer to the information system (Mergin Maps) for the purpose of operational work in the forest.

5 References

Bajić, A., 2008. Olujni vjetar u Hrvatskoj. Zagreb.

Chirici, G., Bottalico, F., Giannetti, F., Del Perugia, B., Travaglini, D., Nocentini, S., ..., Gozzini, B., 2018. Assessing forest windthrow damage using single-date, post-event airborne laser scanning data. Forestry: An International Journal of Forest Research 91 (1), 27-37.

Dalponte, M., Marzini, S., Solano-Correa, Y.T., Tonon, G., Vescovo, L., Gianelle, D., 2020. Mapping forest windthrows using high spatial resolution multispectral satellite images. International Journal of Applied Earth Observations and Geoinformation 93, 102206.

Einzmann, K., Immitzer, M., Böck, S., Bauer, O., Schmitt, A., Atzberger, C., 2017. Windthrow Detection in European Forests with Very High-Resolution Optical Data. Forests 8 (1), 21.

Gardiner, B., 2013. Introduction. In: Gardiner B., Schuck, A., Schelhaas, M. J., Orazio C., Blennow, K., Nicoll, B. (Eds.), Living with storm damage to forests, European Forest Institute, Joensuu, Finland, pp. 11-14.

Hamdi Z.M., Brandmeier, M., Straub C., 2019. Forest Damage Assessment Using Deep Learning on HR Remote Sensing Data. Remote Sensing 11 (17), 1976.

Kislov, D.E., Korznikov, K.A., 2020. Automatic Windthrow Detection Using VH Resolution Satellite Imagery and Deep Learning. Remote Sensing 12 (7), 1145.

Maxwell, A. E., Warner, T. A., Fang, F., 2018. Implementation of machine-learning classification in remote sensing: An applied review. International Journal of Remote Sensing 39 (9), 2784-2817.

Olofsson, P., Foody, G. M., Herold, M., Stehman, S. V., Woodcock, C. E., Wulder, M. A., 2014. Good practices for estimating area and assessing accuracy of land change. Remote sensing of Environment 148, 42–57.

Pilaš, I., Gašparović, M., Novkinić, A., Klobučar, D., 2020. Mapping of the Canopy Openings in Mixed Beech–Fir Forest at Sentinel-2 Subpixel Level Using UAV and Machine Learning Approach. Remote Sensing 12 (23), 3925.

Rüetschi, M., Small, D., Waser, L.T., 2019. Rapid Detection of Windthrows Using Sentinel-1 C-Band SAR Data. Remote Sensing 11 (2), 115.

Stanturf, J.A., Conner, W., Coyle, D.R., Scott, G., 2024. Forest disturbances, McNulty, S. G. (Ed.), Future Forests, Elsevier, 2024, pp. 125-150.

Šimić Milas, A., Rupasinghe, P., Balenović, I., Grosevski P., 2015. Assessment of Forest Damage in Croatia using Landsat-8 OLI Images. South-east European forestry: SEEFOR 6 (2), 159-169.

Ulanova, N.G., 2000. The effects of windthrow on forests at different spatial scales: a review, Forest Ecology and Management 135 (1-3), 155-167.

Vajda, Z., 1974. Nauka o zaštiti šuma. Zagreb.

Whyte, A., Ferentinos, K.P., Petropoulos, G.P., 2018. A new synergistic approach for monitoring wetlands using Sentinels -1 and 2 data with object-based machine learning algorithms. Environmental Modeling & Software 104, 40-54.