

## Mon22-096

## Mapping fire severity over heterogeneous forested landscapes in the Eastern Ukraine to support postfire forest management

*\*V. Myroniuk (National University of Life and Environmental Sciences of Ukraine), S. Zibtsev (National University of Life and Environmental Sciences of Ukraine), O. Soshenskyi (National University of Life and Environmental Sciences of Ukraine), V. Gumeniuk (National University of Life and Environmental Sciences of Ukraine), R. Vasylyshyn (National University of Life and Environmental Sciences of Ukraine), D. Bidolakh (Department of Forestry and Landscape-park Management, Separated Subdivision of National University of Life and Environmental Sciences of Ukraine)*

**SUMMARY**

This paper examines the remote sensing-based approach for mapping burned areas and tracking delayed changes in vegetation conditions after the wildfires of 2020 in the Luhansk region, Ukraine. The field-based fire severity indices (i.e., CBI and GeoCBI) collected through stratified random sampling (regarding the pre-fire land cover) were combined with Sentinel 2 data (dNBR) to map fire severity levels. The GeoCBI index performed better than the CBI in terms of combined use with satellite data. We adjusted the thresholds of dNBR values based on the GeoCBI index and classified burned areas into three levels of fire severity. Comparing the assessment of the fire severity circa 2021 versus 2020, the delayed forest dieback was identified in dry and moist conditions, while forests under wet site conditions showed certain potential for recovery. The study demonstrated a potential for the application of the results (e.g., methodology, reference data, calibrated dNBR thresholds) in a preliminary assessment of the war-caused wildfire effects on forest ecosystems and postfire forest management in the region.



## Introduction

Assessing wildfire effects over large areas is important to quantify a loss of ecosystem services and properly plan restoration activities. Different levels of fire interactions with vegetation over heterogeneous landscapes result in a very variable magnitude of fire damage, which is commonly assessed using satellite data and burn severity indices (De Santis & Chuvieco, 2009; Key & Benson, 2006; Miller & Thode, 2007). An accurate estimation of the fire effects on vegetation, however, needs precise calibration of mapping algorithms using field sampling (Saulino et al., 2020). Recent studies showed that burn severity evaluated for areas with different pre-fire cover (e.g., grass, shrubs, forest, etc.) using satellite-based fire severity indices may be confusing. For example, Stambaugh et al. (2015) admitted various interpretations of the fire severity classes for grasslands and woodlands. Therefore, some studies proposed a fire severity classification scheme based on tree mortality that can be combined with remote-sensed data for mapping forest fires (Whittier & Gray, 2016).

During the last two decades, the occurrence of wildfires in Ukraine has increased. Extreme wildfires in Luhansk oblast (region) in 2020 posed a significant threat to the forested landscapes in the region. This promoted efforts for comprehensive evaluation of the fire severity and planning forest restoration activities within the burned areas (Soshenskyi et al., 2022). Russian invasion of Ukraine in 2022 has radically increased the problem of wildfires throughout the occupied territories. In this situation, the spatially explicit information on burned areas can be collected only using remote sensing technologies. The current study demonstrates the approach for site-specific calibration of burn indices that can be used for the satellite-based assessment of burned areas in the Luhansk region and further postfire forest management.

## Material and Methods

The study is based on a combined use of field data, multisource satellite data, and auxiliary forest inventory information to map fire severity within areas burned in extreme wildfires of 2020 in the Luhansk region. We used Suomi NPP VIIRS and MODIS MOD/MYD14 data on thermal anomalies to determine the dates when the fires started. Based on this, two large fires were identified in 2020 near Sievierodonetsk city. The start date of the first fire (July 6, 2020) as well as the date of suppression of the second fire (October 9, 2020) were used to determine a time interval to collect spectral data. Then, PlanetScope multispectral satellite images (*Planet Team, 2017*) were utilized to visually determine approximate perimeters of burned areas (areas of interest; AOI).

Within the outlined AOI, a pre-fire (October 16, 2019) and two post-fire (October 15, 2020 and October 30, 2021) mosaics of Sentinel 2 L2 surface reflectance images were created. The selected images were cloudless, so no cloud filtering was applied to create cloud-free mosaic composites. The dNBR index (Key & Benson, 2006) was applied to classify the fire severity as a difference between the pre-fire and post-fire NBR values. The NBR index was calculated for each mosaic using NIR and SWIR2 bands of the Sentinel 2 images. Preliminary, the burned areas were classified into three levels of fire severity using the original dNBR thresholds (Key & Benson, 2006): high ( $\geq 0.660$ ), moderate ( $0.270 \div 0.659$ ), and low ( $0.100 \div 0.269$ ). According to this, the first post-fire mosaic of 2020 was used to evaluate the immediate effect of the fire (initial assessment), while the second one of 2021 was incorporated to track delayed vegetation mortality or recovery (extended assessment).

The forest inventory enterprise (PA Ukrderzhlisproject) database was used to design a sampling frame for collecting reference data. These data were used twofold: i) to assess the accuracy of fire severity maps, and ii) to incorporate mapped fire severity in postfire forest management based on levels of fire exposure on various forest types. Thus, we stratified burned areas into six homogeneous land cover categories for which a unified postfire forest management strategy could be applied. We defined four forested categories (73% of the burned area) regarding soil moisture, site fertility and dominant

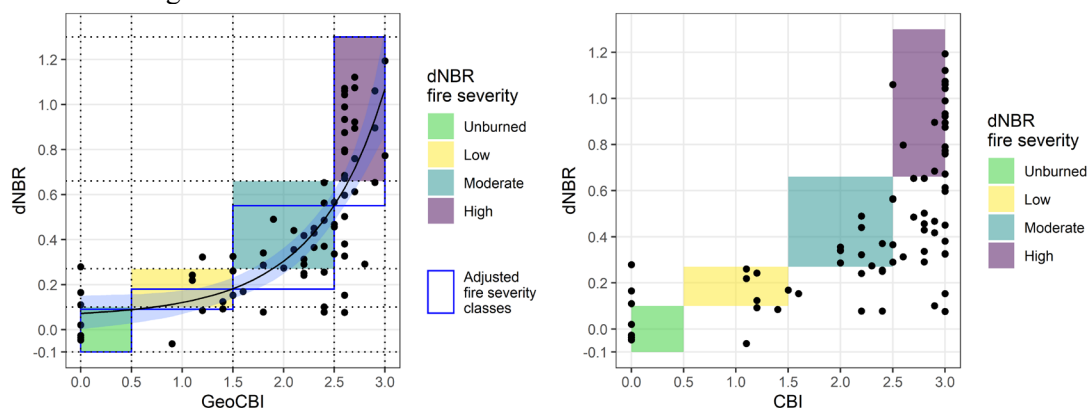


species (i.e., pine or deciduous forest types on sites of various soil moisture), temporally unforested areas (9% of the burned area), and other areas not covered by woody vegetation (18% of burned area). The stratified field sampling was designed so that it proportionally (to the area of a land category) represents different types of land cover and the fire severity (Olofsson et al., 2014). At least three samples were taken in the strata (land category – burn severity), while their maximum number reached 14–18. In total, 73 plots were sampled including seven reference plots outside the burned areas. The fire severity was assessed at each sample plot using the composite burn index (CBI) (Key & Benson, 2006) and its modified version, namely the GeoCBI index (De Santis & Chuvieco, 2009). Both indices are a comprehensive scoring of the fire severity expressed as the total value of disturbance level assessed for various layers of live and dead components of the vegetation. The average post-fire conditions were visually assessed on sample sites within a radius of 15 m by five distinct layers: litter; herbs, low shrubs, and trees less than one meter in height; tall shrubs and trees of 1–5 meters in height; intermediate trees (subcanopy); large trees (upper canopy). These attributes were evaluated in numerical scores from zero (unburned) to three (completely burned). The GeoCBI additionally considered the fraction of cover (FCOV) of each layer.

Based on a pairwise comparison of field-based fire severity indices and dNBR for each sample plot, the accuracy of maps was evaluated using confusion matrices. Then, we adjusted thresholds for fire severity classes using relationships between field-based and satellite-derived indices. We fitted a nonlinear regression model from Miller & Thode (2007) to characterize the linkage between dNBR values and fire severity evaluated in the field. Parameters of the model were predicted in the R statistical software using nonlinear least squares estimation and bootstrap procedures (James et al., 2013). We used 1000 random samples withdrawn from the original data set with replacement, refitted the model for each sample, and evaluated the median, quantiles, and standard errors of the regression coefficients. These allowed us to derive 95% confidence interval of the fitted dNBR values against the field-based index.

## Results

We identified more agreement between dNBR fire severity levels and those evaluated on the field using GeoCBI than CBI index (Fig. 1). The confusion among all severity levels was revealed for the CBI. For the GeoCBI, this was mostly observed between low and moderate severity levels. To adjust thresholds for fire severity and obtain a less biased classification of the Sentinel 2 data, dNBR were further modelled against field measured GeoCBI values.

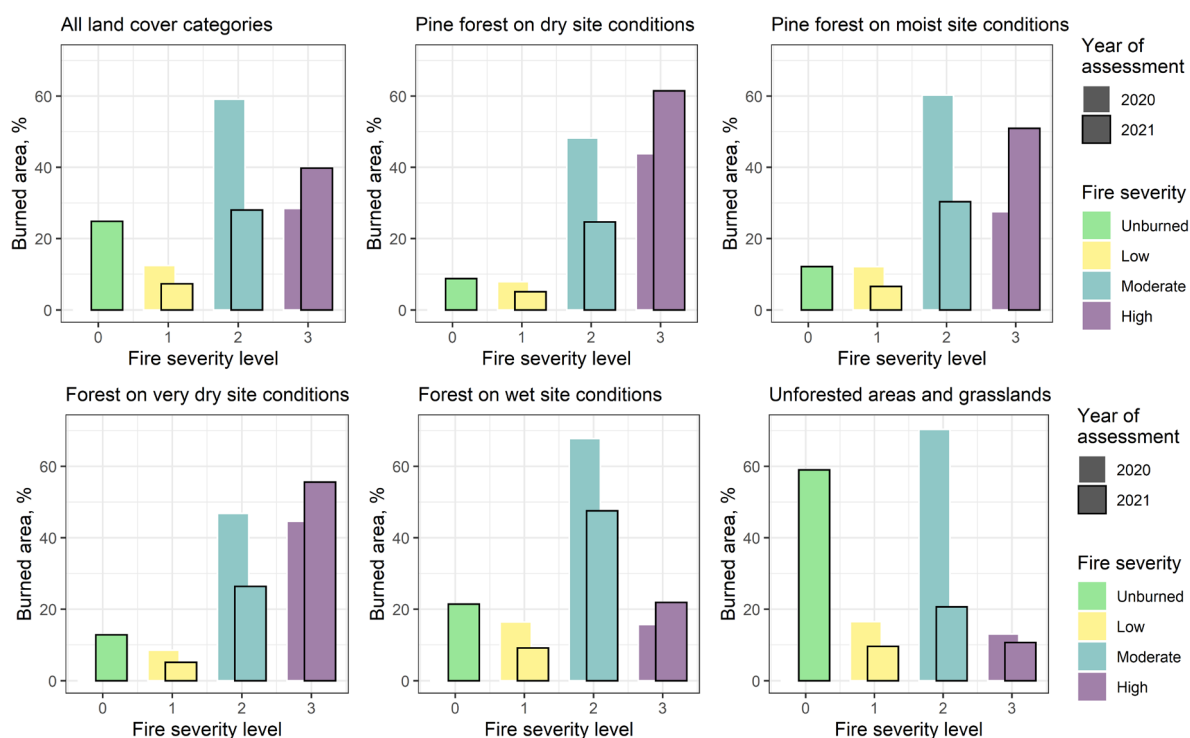


**Figure 1** Agreement between the field-based and remote sensing-derived fire severity classes: points show the actual empirical data; line and ribbon plot on the background represent an average forecast with 95% bootstrap confidence interval of the agreement; blue rectangles depict the adjusted boundaries of burn severity classes based on the field sampling (Y-axis). The thresholds of fire severity classes observed on site (X-axis) were used according to De Santis & Chuvieco (2009) for GeoCBI and Key & Benson (2006) for CBI



We adjusted the predicted thresholds of the dNBR index (blue rectangles) and reclassified the Sentinel 2 mosaic. In this study, the following thresholds for the fire severity levels were established: high ( $\geq 0.550$ ), moderate ( $0.180 \div 0.549$ ), and low ( $0.090 \div 0.179$ ). As a result, the overall accuracy of the fire severity mapping in 2020 increased from 49% (original thresholds of the dNBR) to 70% (adjusted thresholds through field sampling).

The 95% confidence intervals of the adjusted dNBR thresholds were used to indicate the degree of uncertainties in our assessment of burned areas. According to the assessment, the distribution of the burned areas in 2020 among the fire severity levels was as follows: low – 5,016 ha ( $2,374 \div 4,703$  ha); medium – 24,088 ha ( $22,999 \div 23,361$  ha); high – 10,466 ha ( $8,003 \div 13,836$  ha). The land cover information extracted from the forest inventory database was used to track the re-distribution of burned areas among the fire severity levels in 2020 and 2021 (Fig. 2). Unforested areas and other not covered by woody vegetation areas (grasslands) demonstrated a great potential for regeneration during the first year after the fire. In opposite, all forested areas exhibited more delayed mortality than recovery. This is justified by an increased proportion of the high level and decreased proportion of the moderate level of the fire severity in 2021. The extended assessment revealed a certain potential for forest recovery only in wet soil conditions.



**Figure 2** Initial (2020) versus extended (2022) assessment of fire severity

The obtained results indicate the potential strategy for postfire forest management in the region. Due to the high probability of forests dieback with the severe fire impact, immediate salvation logging must be applied there, while selective sanitary cuttings could be used in forests with the moderate fire severity aimed to support natural regeneration of mixed pine-hardwoods stands. Given the higher potential for vegetation recovery on fertile and wet soil sites, there is also a good potential for natural forest regeneration.



## Conclusions

This work demonstrates the first attempt in Ukraine for spatially explicit assessment of fire severity based on combined use of field-based and remote-sensed data. The proposed approach provides the foundation for mapping burned areas within similar landscapes using adjusted through field sampled thresholds of the dNBR values. Regarding the ongoing war, forestry in Ukraine is facing challenges because of a need for a comprehensive assessment of forest damage on large areas the access to which are restricted or dangerous. Thus, there is a potential for implications of the results of this study for a preliminary assessment of collateral damage from the war, including fire severity over such territories.

## Acknowledgements

This project supported by USAID Economic Resilience Activity. We would like to thanks to foresters of Luhansk region for their cooperation and providing logistic support of field work.

## References

- De Santis, A., & Chuvieco, E. (2009). GeoCBI: A modified version of the Composite Burn Index for the initial assessment of the short-term burn severity from remotely sensed data. *Remote Sensing of Environment*, 113(3), 554–562. <https://doi.org/10.1016/j.rse.2008.10.011>
- James, G., Witten, D., Hastie, T., & Tibshirani, R. (Eds.). (2013). *An introduction to statistical learning: With applications in R*. Springer.
- Key, C. H., & Benson, N. C. (2006). *Landscape Assessment (LA): Sampling and Analysis Methods (General Technical Report RMRS-GTR-164; FIREMON: Fire Effects Monitoring and Inventory System, p. LA-1-LA-51)*. Rocky Mountain Research Station, US Department of Agriculture, Forest Service.
- Miller, J. D., & Thode, A. E. (2007). Quantifying burn severity in a heterogeneous landscape with a relative version of the delta Normalized Burn Ratio (dNBR). *Remote Sensing of Environment*, 109(1), 66–80. <https://doi.org/10.1016/j.rse.2006.12.006>
- 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. <https://doi.org/10.1016/j.rse.2014.02.015>
- Planet Team (2017). *Planet Application Program Interface: In Space for Life on Earth*. San Francisco, CA. <https://api.planet.com>
- Saulino, L., Rita, A., Migliozzi, A., Maffei, C., Allevato, E., Garonna, A. P., & Saracino, A. (2020). Detecting Burn Severity across Mediterranean Forest Types by Coupling Medium-Spatial Resolution Satellite Imagery and Field Data. *Remote Sensing*, 12(4), 741. <https://doi.org/10.3390/rs12040741>
- Soshenskyi, O., Myroniuk, V., Zibtsev, S., Gumeniuk, V., & Lashchenko, A. (2022). Evaluation of Field-Based Burn Indices for Assessing Forest Fire Severity in Luhansk Region, Ukraine. *Ukrainian Journal of Forest and Wood Science*, 13(1), in press.
- Stambaugh, M., Hammer, L., & Godfrey, R. (2015). Performance of Burn-Severity Metrics and Classification in Oak Woodlands and Grasslands. *Remote Sensing*, 7(8), 10501–10522. <https://doi.org/10.3390/rs70810501>
- Whittier, T. R., & Gray, A. N. (2016). Tree mortality based fire severity classification for forest inventories: A Pacific Northwest national forests example. *Forest Ecology and Management*, 359, 199–209. <https://doi.org/10.1016/j.foreco.2015.10.015>

