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Monitoring of Fires Caused by War in Ukraine Based on Satellite Data

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***Abstract* — The focus of this paper is on fire monitoring studies which utilize a variety of satellite data. The study examines various data sources that are used to automatically detect fires at a national level in Ukraine. Existing fire monitoring systems have low spatial resolution, which makes it difficult to detect fires. Therefore, the authors propose an approach that uses both low- and high-resolution satellite data for fire monitoring. The study found that MODIS, Landsat-8,9 and Sentinel-2 satellite data provide reliable information for fire monitoring in Ukraine. These data sources offer a variety of benefits, including high spatial resolution, frequent revisit times, and wide spectral coverage. In order to understand how favourable weather conditions are for the occurrence of fire, the authors used the Fire Potential Index (FPI). The methodology developed in this study provides a promising approach to monitoring fires and understanding the causes of fires, particularly those caused by the war in Ukraine. The authors implemented the fire detection methodology and FPI index assessment in the Google Earth Engine cloud platform, which allowed for efficient processing and analysis of large volumes of data. In conclusion, the paper highlights the importance of using a combination of low- and high-resolution satellite data for fire monitoring.**

Keywords* — *burnt area, Sentinel-2, Landsat-9, FIRMS, Land Surface Temperature, Fire Potential Index

I. INTRODUCTION

Environmental deterioration has been observed in recent years as a result of ex-tensive fires. This underscores the significance of detecting and monitoring fires, particularly those occurring in forests, as well as managing their propagation. One effective solution for this issue is through the use of satellite data. Numerous examples of successful fire monitoring techniques have emerged globally, with many relying on AVHRR data from NOAA satellites [1]. Various techniques for monitoring and con-trolling fires, including forest fires, have been developed in recent years due to the environmental degradation caused by large-scale fires. Among the most commonly used satellites for this purpose are MODIS (TERRA and AQUA satellites) and VIIRS (Suomi NPP and NOAA-20 satellites) [2]-[4].These techniques are integrated into monitoring systems such as the NASA Fire Information for Resource Management System (FIRMS) [5]-[7]. The advantage of MODIS and VIIRS data is that they can provide real-time monitoring of fire propagation, with data updating every 3 hours. This information can also be accessed via other NASA resources such as WorldView. The MODIS system provides daily fire data with a spatial resolution of one square kilometer, which is useful for detecting hot spots caused by wildfires and other high-temperature events [8]. However, the system does not guarantee that a detected hotspot is indicative of an ongoing fire. The SPOT-VGT data from the SPOT satellite is another frequently used source [9], although its low spatial resolution is a disadvantage. With the launch of Landsat-8,9, this satellite will also become a valuable data source for fire monitoring, as it has a 100m spatial resolution in thermal infrared channels [10]. Although this data can be scaled down to 30 m, the revisit time of once every eight days may be too long for near-real-time monitoring. This paper [11] presents an algorithm that uses Landsat data to identify burned areas, which can be applied anywhere Landsat and training data are available. The algorithm generates burn probability surfaces using band values and spectral indices, and pixel-level thresholding combined with a region growing process is used to generate burn classifications. BAECV products were generated for the conterminous United States from 1984 through 2015, which mapped more burned area than existing Global Fire Emissions Database (GFED) and Monitoring Trends in Burn Severity (MTBS) data. The BAECV products document patterns of fire occurrence and its impacts on natural and human systems and are expected to be useful to studies seeking to understand them. The 10-meter spatial resolution of Sentinel-2 data allows for the detection of fires in their early stages and provides updates every five days. Due to their high spatial resolution, collecting and storing data for a country's territory over a long period of time can be challenging and require significant processing resources. This article [12] presents the initial findings of a study that examined the use of spectral indices to assess the severity of a forest fire that occurred in Madeira Island in August 2016. The results indicated a strong correlation between the spectral indices and Copernicus Emergency Management Service (EMSR175) analysis, which was considered as the reference truth. The study suggests that Sentinel-2 could be a valuable tool for monitoring post-fire conditions.

In connection with the war in Ukraine, which began on February 24, 2022, the de-termination of the cause of the fire - due to dry weather conditions [13], [14] or due to active military operations - is currently also an urgent issue. To solve this issue, it is proposed to use the Fire Potential Index (FPI) [15], which makes it possible to predict the weather conditions due to which fires occur. While the FPI is a useful tool for predicting fire occurrence, it does not always accurately predict the location of fires. Fires can occur in unexpected locations, and can be caused by a variety of factors, including human activity, lightning strikes, and other natural causes. For Ukraine, most of the fires were caused by war. Since military operations are taking place in the southern and eastern territories of Ukraine, more attention will be devoted to them.

II. Data

A. Satellite data

Optically corrected Sentinel-2 Level 2A satellite data, featuring a revisit period of 5 days, is employed to identify fire locations and burned areas. Along with a Lev-el-2A surface reflectance product, Sen2Cor offers an 11-class Scene Classification (SCL) map [16]. The data presented in this map hold significant value for automated processing methodologies. It served as a cloud and shadow mask, enabling the extraction of clear land pixels from the Sentinel-2 imagery.

This study utilizes the MODIS Fire Information for Resource Management System (FIRMS) [5] as the primary data source for identifying hot spots of fire activity. FIRMS was established in 2007 by the University of Maryland with financial support from NASA's Applied Sciences Program and the United Nations Food and Agriculture Organization (UN FAO) to offer timely and accurate active fire location information to natural resource managers who faced difficulties in obtaining satellite-derived fire data.

Data from Landsat-8, -9 satellites, namely band B10 (Thermal infrared, resampled from 100m to 30m) are used to validate the created burn area mask [17]. Given the fact that the Landsat-8 and -9 together revisit time is 8 days, which is almost two times less often than Sentinel-2, the validation was carried out selectively for cloud-free images and for the test part of the territory.

B. Land cover classification

To identify the type of land cover affected by fires, a land cover map is used, which was created by using cloud technologies and neural network models [19], [19]. SAR Sentinel-1 descending data 4 bands (Red B4, Green B3, Blue B2, InfraRed B8) of Sentinel-2 data with preprocessing Level-2A and 10-meters spatial resolution are used for classification map creation. The multilayer perceptron (MLP) is used for training neural network.

C. Vector Data With Boundaries of Fires From Shelling

In order to validate the map of burned areas, within this work used the provided vector data with fires created on the basis of high-resolution satellite data (Planet / WorldView-3), and Sentinel-2 data were used to detect the date of the fire. This data set represents fires from shelling in the south and east of Ukraine in 2022. These data collected within "Satellites for Wilderness Inspection and Forest Threat Tracking" (SWIFTT) project.

III. Methodology

A. Fire and burn are detection

The use of FIRMS data makes it possible to determine the potential areas for which fires are possible. In our case, we used all pixels (that is, with probability be-tween 0 and 100). What made it possible to create a Hotspots mask for the territory of Ukraine. However, due to the low spatial resolution, this fire mask needs to be improved. The general scheme for creating a fire mask is presented in Fig. 1.

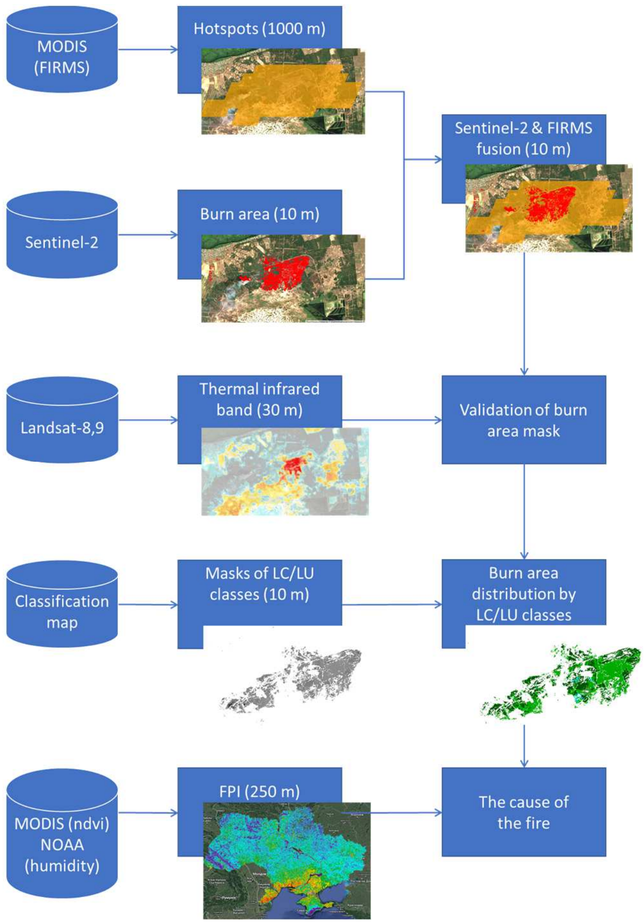


Fig. 1. The general scheme of creating a fire mask based on satellite data.

In order to enhance the precision of fire location and burn area determination, we utilized products obtained from Sentinel-2 satellite data. Specifically, we relied on the Normalized Burn Ratio (NBR) index [20] as the foundation for our approach. Initially, we calculated NBR indices for the region affected by the fire (during and after fire) for each i-th image:

$$NBR_{pre} = \frac{B8 - B12}{B8 + B12},\ NBR_{post_i} = \frac{B8_i - B12_i}{B8_i + B12_i}. \quad (1)$$

Fire detection was conducted based on the ratio for each individual i-th image:

$$Fire_i = \frac{NBR_{pre} - NBR_{post_i}}{NBR_{pre} + 1.001} \geq threshold. \quad (2)$$

Having received a mask of burnt areas according to Sentinel-2 data and potential areas according to FIRMS data, we consider those pixels at the intersection of these two received data sets to be reliable.

In order to validate the received fire mask, it is suggested to use temperature data based on Landsat-8 and -9 satellites. Thermal infrared band (resampled from 100m to 30m) was used in this methodology. To determine the fire, the maximum temperature for the studied area is determined and the temperature with low values is filtered. After that, the validation of the fires obtained from the Sentinel-2 data is carried out, taking into account the limited available data due to cloud cover and the low regularity of Landsat satellite.

B. *Fire Potential Index (FPI)*

The Fire Potential Index (FPI) model was utilized to identify regions with the highest likelihood of fires. The formula employed for its calculation is as follows [15]:

$$FPI = (1 - FM_f) \cdot (1 - LR) \cdot 100 \tag{3}$$

where FM_f - represents fuel moisture, where fuel refers to the type of land cover, and Live Ratio (LR) determines the ratio of living vegetation to dead vegetation. LR is determined using the following formula:

$$LR = RG_f \cdot LR_{mx} / 100 \tag{4}$$

The following formula was utilized to determine Relative Greenness (RG_f), which is then converted into a fractional value, RG/100, in order to obtain an estimate of the proportion of green vegetation in a given area. RG is calculated using NDVI indices derived from MODIS data:

$$RG = \frac{ND_0 - ND_{mn}}{ND_{mx} - ND_{mn}} \cdot 100 \tag{5}$$

The equation involves the use of ND_0, which represents the maximum NDVI value observed during the analyzed time period, as well as ND_{mn} and ND_{mx}, which denote the minimum and maximum NDVI values, respectively, recorded at the specific pixel's location over time. More details about the FPI calculation methodology can be found in the work [15].

To determine the type of land cover, a classification map for the territory of Ukraine with a spatial resolution of 10 m was used. The fire detection methodology described above using satellite data is implemented on the Google Earth Engine cloud platform.

IV. Results

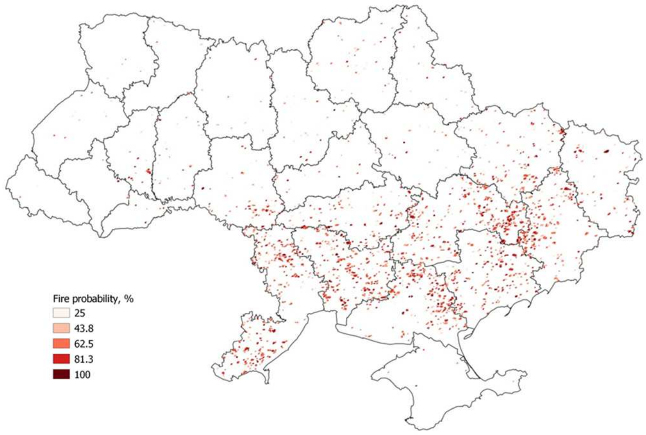
A. *Fires hotspot according to FIRMS data*

The Fig. 2 shows the distribution of fires determined according to FIRMS data for summer 2021 (01.06.2021 – 30.08.2021) and 2022 (01.06.2022 – 30.08.2022). As can be seen from the geographical location of the identified hot spots, in 2022 they are located and most concentrated along the lines of hostilities. That is why additional research into the possibility of determining the cause of the fire was included in this work. In particular, whether the weather conditions contributed to their occurrence.

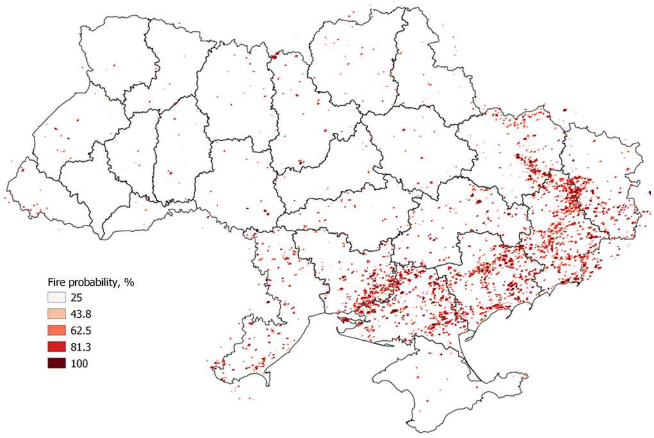
B. *Burned area based on Sentinel-2 data*

The overall burned area was estimated to be 104.2 thousand hectares as of 15-18 July, based on Sentinel-2 data. This includes approximately 70 thousand hectares of cereal crops, 0.26 thousand hectares of rapeseed, 7.8 thousand hectares of summer crops, 25 thousand hectares of grassland, and 1.1 thousand hectares of forest. However, the Sentinel-2 estimates represent a lower estimate only, as cloud cover during satellite surveys may have affected the accuracy of the results. Given that the average wheat harvest in 2021 was 45.3 tons per hectare (according to the State Statistical Service of Ukraine), and that the fires occurred during the wheat and barley harvest period, the potential losses due to fires along the front line are estimated to be 3.17 million quintals or 317 thousand tons of grain.

To validate our approach to creating a fire mask from satellite data, we used vector boundaries with forest fires caused by shelling. In particular, for the south of Ukraine (mainly the Kherson region), the forest was most affected in the month of May. The obtained overall accuracy is 95.5%.



a) 01.06.2021 – 30.08.2021



b) 01.06.2022 – 30.08.2022

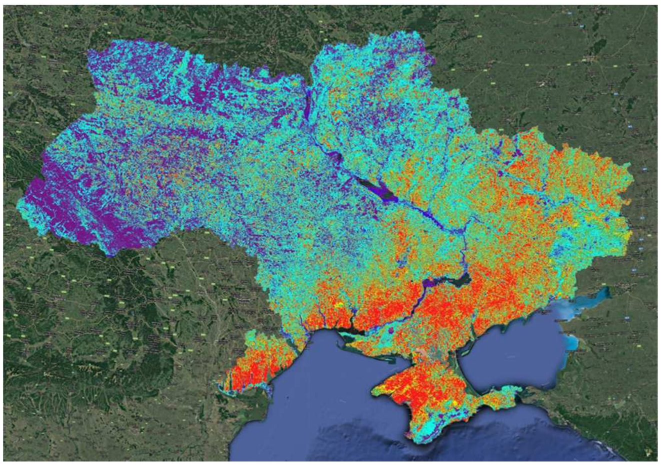
Fig. 2. Hotspots for Ukraine based on MODIS FIRMS data for a) 2021 and b) 2022 for June – August.

C. *FPI index*

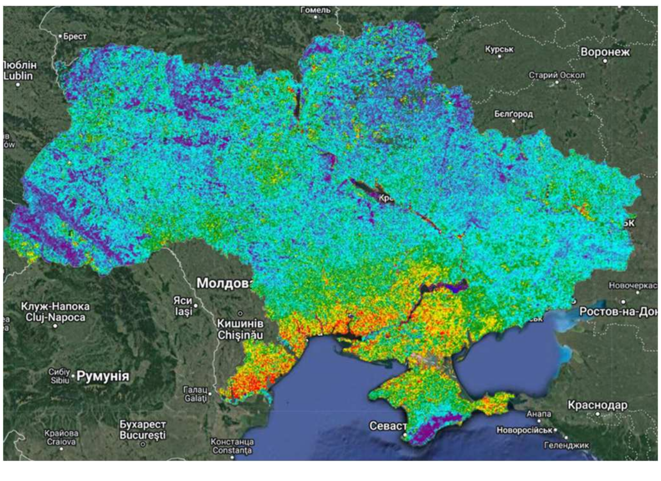
Using satellite data and a land cover classification map, a Fire Potential Index was created for the territory of Ukraine for 2021 and 2022. For this, the Google Earth Engine cloud platform was used. The resulting index is a raster map with a spatial resolution of 250 m, containing values from 0 to 100 that indicate the probability of fire occurrence. Fig. 3 shows these maps, where blue values have low values and red values have high values [21].

Observations from the provided image reveal that during the summer of 2021, Ukraine predominantly experienced fires dispersed across its southern and eastern regions, aligning with the Fire Potential Index. Factors contributing to these fires included meteorological conditions, as anticipated by the Fire Potential Index, and anthropogenic influences such as stubble burning in agricultural fields. On the other hand, in 2022, noticeable deviations are observed, the Fire Potential Index indicates possible fires related to weather conditions only in the southern districts of Mykolaiv, Kherson and Odesa regions. Actual fires appear to trace a front line, suggesting their origin as a consequence of human activities like rocket and bomb usage.

The results for 2021 show a correlation FPI with real fires - 0.66, and factors contributing to these fires included meteorological conditions, as anticipated by the Fire Potential Index, and anthropogenic influences such as stubble burning in agricultural fields. For 2022 the correlation is 0.25 for all oblasts. This is a rather low value and at first glance one may get the impression that there is no connection. But if we exclude oblasts in which active hostilities are taking place (Luhanska, Mykolaivska, Zaporizka, Kharkivska, Donetska, Khersonska), the correlation coefficient for 2022 will be 0.68. So, in 2022, the correlation is low due to the eastern and southern oblasts, and in all other territories the trend remains the same as for 2021. This confirms, not only visually, that the fires in these regions did not arise from natural causes, but that most of the main reasons for such fires are military events in those territories.



a) 01.06-31.08.2021



b) 01.06-26.07.2022

Fig. 3. Fire Potential Index summer 2021 and 2022.

V. CONCLUSION AND FUTURE WORK

The results presented in this article demonstrate the effectiveness of using satellite data and land cover classification maps to create a Fire Potential Index, which provides a probability of fire occurrence for different regions of Ukraine. The Fire Potential Index was created for the years 2021 and 2022, and the resulting maps showed a correlation between the areas with high probability of fire occurrence and the actual fire events in Ukraine in 2021, and no correlation for 2022 which shows that weather conditions are not the cause of fires. The study also found that the majority of fires in 2022 occurred along the front line, indicating that they were human-caused by rockets and bombs, rather than weather conditions.

Possible further research is to use the Sentinel-1 radar data to solve the cloud issue from Sentinel-2 optical data, as well as the use of more modern indices to determine the fire danger [22], [23].

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