War Damage Detection Based on Satellite Data

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Abstract: As a result of the resolution of the armed military conflict on the territory of Ukraine on February 24, 2022, the agricultural infrastructure of the latter was marked by large-scale destruction. Thousands of hectares of fields, the harvest from which previously provided both domestic and world needs, were mined, destroyed, damaged by artillery shelling, explosions and movements of military equipment. To restore the affected areas to ensure food security of Ukraine and the world, the state government, with the support of international organizations, must correctly distribute financial resources between affected landowners and farmers. For this, there is a need for accurate identification of war-affected territories. This task can be effectively performed using remote sensing data. In this work, damage to agricultural fields due to military operations is searched for by calculating the relative difference of the vegetation indices based on Sentinel-2 satellite data. Cloud-free composites of normalized difference vegetation index (NDVI) are compared for the nearest period before and after active hostilities in a specific area (dates and locations are obtained from the ACLED source). Pixels whose relative difference exceeds a given threshold are considered damaged. The survey of the country's territories was conducted from February 24 to September 25, 2022, dividing the dates into biweekly periods. According to the results of the research, such damage to agricultural fields as craters from explosions and shelling, traces of machinery, burnt fields, etc., were found. The relative difference between the minimum and average values of vegetation indices in the affected areas averaged 25% versus 15% for the minimum period before and after the lesion. The detected damaged areas were validated using ACLED data. It was determined that more than 50% of the total number of areas identified as damaged were located within a radius of up to 5 km from the zone of combat activities.

1 INTRODUCTION

After the invasion of the enemy troops of the Russian Federation on the territory of Ukraine on February 24, 2022, a large part of the country was damaged, including not only cities and important infrastructure facilities, but also agricultural fields. In the territories where active hostilities are taking place, most of the agricultural land is mined and unsuitable for growing products. This was a big blow both for the agro-industrial complex of Ukraine and caused a shortage of food products on the European markets, because Ukraine was one of the leading exporters of agricultural products to Europe for decades in a row.

To mitigate the negative effects of the war on the agricultural sector and ensure food security, the government of Ukraine and the international community decided to allocate funds for the restoration of damaged agricultural lands. To do this, farmers whose lands were affected were asked to fill out questionnaires, and tens of thousands of landowners applied for compensation. However, it is not known for sure which areas were exactly affected by shelling and explosions, because not all farmers accurately declared the amount of their losses and the area of damage, and some did not declare at all. In order to properly distribute the allocated funds, the government needs reliable information and a thorough inspection of the condition of the fields. It is physically impossible to carry out this task in the usual way, by carrying out an actual survey of the territories, due to the excessively large area of land, constant hostilities and occupation. In addition, this is an irrational use of human and material resources.

However, it is possible to solve the problem of detecting damaged areas using remote sensing data [1], [2]. Satellite data allow to identify land use and cover/land use changes using machine learning models [3]. The main advantage of providing remote analysis is safety. In article [4] authors created a framework that can be used to estimate the damage during the ongoing war and get information for restoration planning. As data were used Surface reflectance (SR) images from the Landsat-8 Operational Land Imager and several random forest algorithms were used for extracting needed information. As feature variables are used several indexes such as NDVI, MNDWI, NDBI, BSI. In work [5] authors tried assess damages using several types of optical images and SAR data. Multiple cities in the Kyiv region were chosen as study areas. All process of investigation contains 4 stages for both Sentinel-1 and Sentinel-2 data [6].

Also, according to the previous experience of world scientists, remote sensing data from satellites of medium and high spatial resolution are successfully used to analyze time series of vegetation indexes [7], [8], detect land degradation [9], monitor land use [10], predict land yield and productivity, records of fires, drought [8] and floods, etc. Satellite missions that provide open data for tracking over the territory of Ukraine are Landsat-8 (30m) and Sentinel-2 with a spatial resolution of 10m (data available since 2014).

Using indices calculated from satellite data, in particular the NDVI vegetation index, it is possible to detect abnormal changes in land cover that have occurred within a short period of time [11], and record a sharp decrease in plant growth rates or a drop in the amount of vegetation. These anomalies are usually provoked by weather phenomena, such as hail [7], [12], for example. However, for Ukraine, the changes caused by military actions can be detected by analyzing the time series of vegetation indexes, in particular NDVI [13]. The application of the technique of comparing NDVI in a fixed territory on specific specified dates can help to build an automatic recognizer capable of pixel-by-pixel identification of craters from bomb explosions, eruptions from artillery shelling, tracks from tank tracks, other military equipment, etc [14].

Thus, the topic of this work is the development of an automated tool for the identification of agricultural fields damaged as a result of military actions based on remote sensing data for the analysis of NDVI and spectral channels.

The main purpose of the paper is the accurate detection of damaged areas on the agricultural fields at the pixel level and an adequate assessment of the severity of damage.

The identifier developed in this way will make it possible to adequately assess the consequences of the war in agricultural area and will help to correctly allocate the budget for the restoration of the functioning of the agrarian industrial complex of Ukraine.

2 DATA AND MATERIALS

Data from a wide-area mission with high resolution (10m) and multispectral imagery supporting the Copernicus Land Monitoring study, Harmonized Sentinel-2 MSI level A2 were used to calculate the vegetation index and analyze spectral channels. The images of the collection contain 16 spectral bands. For the study, vegetation index NDVI was calculated, as well as four bands (Red, Green, Blue, and NIR).

Due to overcast areas during numerous satellite surveys, in order to obtain reliable data, there was a need to clear images from clouds and build composites in the shortest possible time.

An open source of information - the Armed Conflict Locations and Events Data (ACLED) project [15] was used to select appropriate dates for the construction of composites before and after potential field damage in order to detect damage to territories by comparing the values of vegetation indexes before and after damage. ACLED collects information on the dates, locations and types of all recorded events of political violence and protests worldwide, including information about the territories of Ukraine where active hostilities are currently taking place. Starting from February 24, the time was divided into biweekly intervals (periods), for each of which the damaged areas were determined (Figure 1). The parcels deliniation polygons developed by the Sinergise company for Ukraine within the EO4UA [16] initiative was used as field contours.

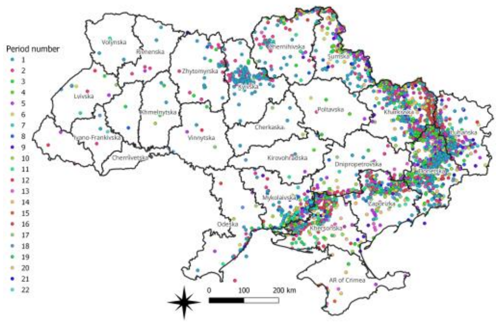

Figure 1: ACLED information about military action in Ukraine for 15 biweekly periods from 24th of February.

Thus, we selected the closest possible time period before the military attack, the date and location of which was provided by ACLED, and the closest period after the military attack to construct a relatively cloud-free satellite data.

3 METHODOLOGY

3.1 Damaged Detection Based on Comparison of NDVI Distribution

The method of detecting fields damaged by military actions on the territory of Ukraine is based on a pixel-by-pixel comparison of NDVI values during the narrowest time interval before and after the impact. NDVI – is a commonly used vegetation index, calculated by near infrared (NIR) and infrared (RED) bands of satellite observations with the (1):

$$NDVI = \frac{NIR-RED}{NIR+RED} \tag{1}$$

After obtaining the indicators of the vegetation index according to two composites - before and after military activities on a specific territory on a regional scale - the relative difference of NDVI in percentages is calculated according to the following (2):

$$dNDVI_t = \frac{NDVI_{t+1}-NDVI_t}{NDVI_t} * 100\%, \tag{2}$$

where: $dNDVI_t$ - is the relative percentage difference of NDVI at point t; $NDVI_t$– NDVI value before potential damage to the territory at point t; $NDVI_{t+1}$- NDVI value after potential damage to the territory at point t.

To calculate the NDVI only within the boundaries of agricultural crops the land cover classification map of 2022 was used. The next step is to set the maximum permissible (threshold) value of the relative difference of NDVI in order to filter out normal changes in vegetation cover and detect anomalies. To remove non-military NDVI changes, we thresholded within a field the number of pixels with a large NDVI drop of 60% of the field size using vector field contours. The previously given vector contours of the fields were reduced by 2 pixels along the perimeter inside, in order to avoid fixing the changes of NDVI in the territories between the fields.

3.2 Damaged Detection Based on spectral Values Distribution

Comparing pre-event and post-event satellite data shows good results in damage monitoring, but there are often situations where no pre-event satellite data is available, or it is all covered by clouds. For such cases, another algorithm has been developed that uses only one image, or rather, its spectral channels separately.

This algorithm works at the level of each individual field within the contours created by the Sinergise company. To begin with, the NDVI indicator is calculated within the contour of the field to determine the state of vegetation according the (1). In case the vegetation is low (NDVI < 0.3), Green and Blue spectral channels are used to damaged territories detection. Otherwise, the Green and NIR channels are used. Further, within each field, the distribution of the values of the corresponding spectral channels is analyzed and those of them that are not statistically average are cut off. In particular, for fields with high vegetation, the following (3) is used:

$$Damaged_{Hight\_vegetation} = \begin{cases} Value_{Green} \le \mu - 2\sigma \\ Value_{Blue} \le \mu - 2\sigma \end{cases}, \tag{3}$$

and for fields with low vegetation, the following (4) is used:

$$Damaged_{Low\_vegetation} = \begin{cases} Value_{Green} \ge \mu + 1.5\sigma \\ Value_{NIR} \ge \mu + 1.5\sigma \end{cases}, \tag{4}$$

where μ - mean channel's value at field level, σ - standard deviation of channel's value at field level. The general scheme of the developed algorithm is shown in the Figure 2.

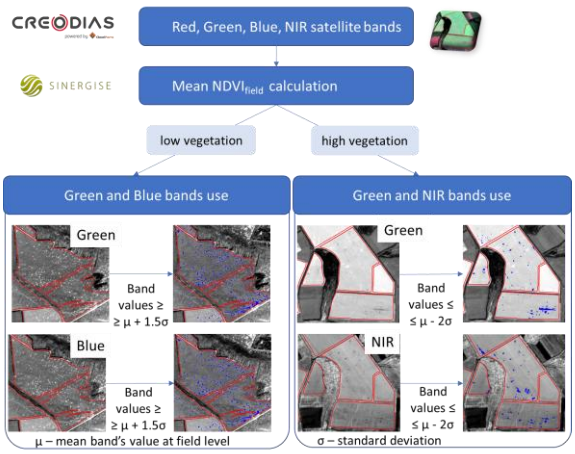

Figure 2: The general scheme for finding damage from bombs and missiles.

To confirm the assumptions about the possible damage to the territories, histograms of the distribution of NDVI in the cadastral boundaries of the target field are constructed according to the available composites in order to estimate the dispersion of the vegetation index and the deviations of the minimum values of NDVI from the average value within the field before and after damage.

4 THE RESULTS

4.1 Damaged Fields Detection

With the help of calculations of the relative difference of the NDVI, we were able to identify damage from artillery fire (Figure 3a), as well as traces of the movement of equipment, burned fields and other numerous damages (Figure 3b).

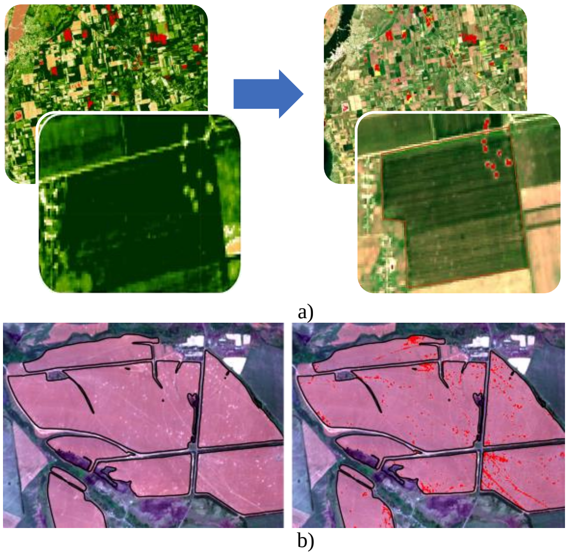

Figure 3: a) Damages detected based on relative difference of NDVI, Kherson region, (May 9 - May 2022). b) Detected damaged fields based on spectral channels, Donetsk region (02 July 2022).

To check the distribution of NDVI within the identified as damaged fields, histograms were constructed, an example of which is shown in Figure 4. The relative difference of the minimum and average NDVI in the affected field from the example (Figure 4b) was about 25% against 17% in the same field before the injury. The relative median difference between the minimum value of affected and uninjured areas on the image in which the damage was recorded was 13% on average (Figure 4c). In general, a similar situation was observed in other fields.

For comparison with the relative difference of NDVI in the unaffected area, we constructed a histogram of the relative difference of NDVI in the nearest neighboring undamaged field for the same date (Figure 5).

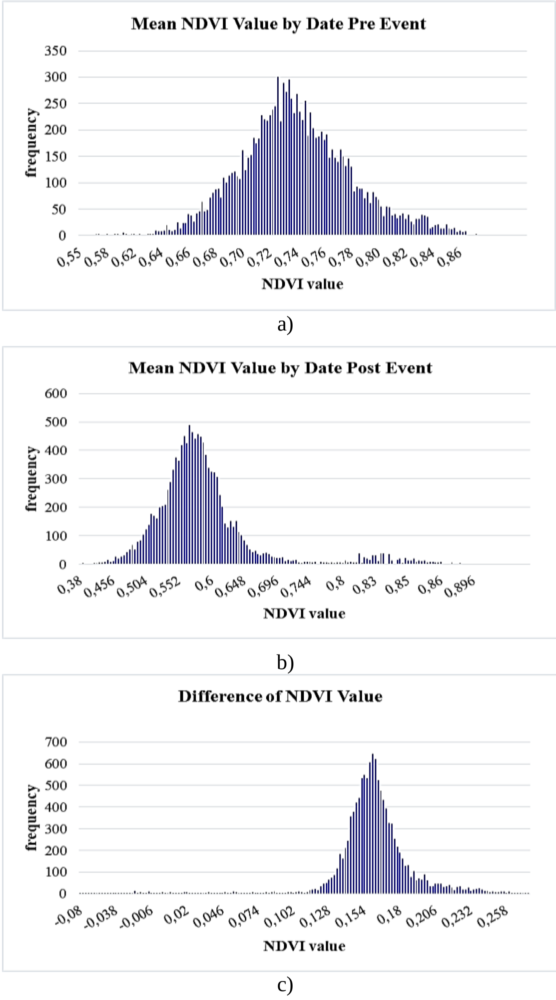

Figure 4: Distribution of NDVI within the field. a) before the event of potential damage (June 1 - June 5); b) after the event of potential damage (June 6 - June 8) damage.; c) The difference in the distribution of NDVI before and after damage.

As can be seen in Figure 5, the largest difference of NDVI on an intact field does not exceed 0.07, while on a damaged field it exceeds 0.26.

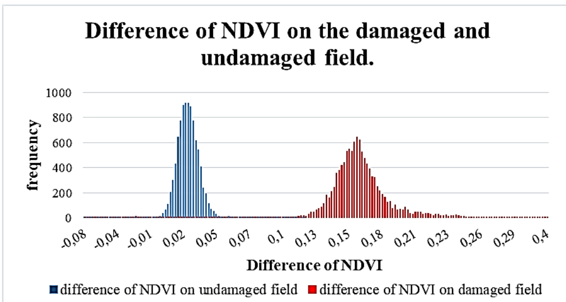

Figure 5: The difference of NDVI on the damaged and undamaged field.

4.2 Comparison of Automatically Recognized Damages and Damages Detected by the Experts

To validate the method of automatic field recognition, we conducted a visual inspection of the damaged areas, using data on the areas and dates of active hostilities for orientation from the ACLED source. To improve the quality of the verification, we will choose the 8th period of the war (6-19 June) as the period of active vegetation and the Donetsk region as the region of active hostilities.

According to the results of a comparison of automatic and "manual" methods for recognizing field damage (Figure 6), it was found that the method based on the calculation of the relative difference of the NDVI identifies many more fields than can be seen on a three-channel satellite image (Figure 7) (on cloudless composites, 2143 fields were automatically identified against 376 fields visually assessed as damaged).

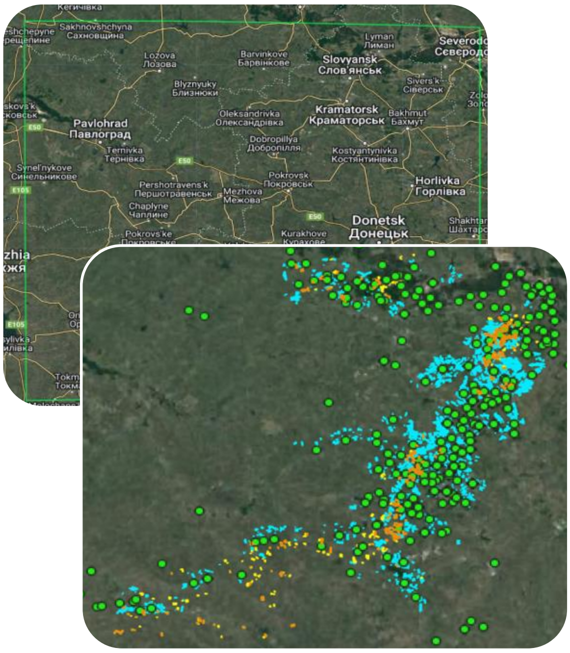

Figure 6: Comparison of fields identified as damaged by an automated method and fields marked as damaged by a "manual" method. Donetsk region, 8th period of the war (June 6 – June 19). Yellow polygons are manually marked fields. Blue polygons are fields recognized as damaged based on data on the relative difference of NDVI, Brown polygons are fields recognized as damaged by "manual" and automatic methods. Green dots show combat zones.

At the same time, the identification results coincided only for 193 fields, which is about 48% of visually recognized as damaged fields and 9% of the number of fields identified as damaged based on the relative difference of NDVI. Such a large difference in results may be explained by clouds, normal seasonal changes in NDVI, tillage, weather conditions, etc., which may have influenced the strongly negative relative difference in NDVI. On the other hand, there is the problem of the imperfection of the human factor, when the fields could not be recognized as damaged or, on the contrary, the surviving areas were marked as damaged. Therefore, for accurate damage recognition results, it is worth combining both methods, first calculating the relative differences of the NDVI, and then re-viewing the marked fields on the RGB satellite image.

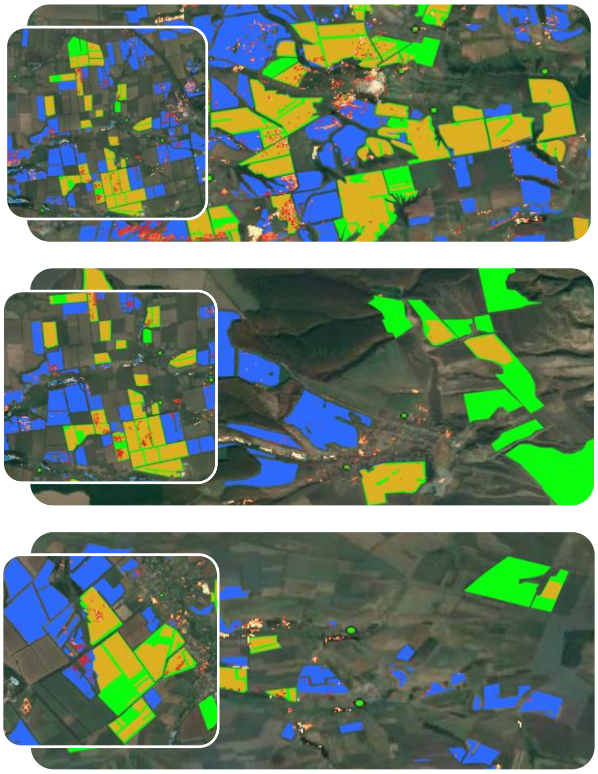

Figure 7: Comparison of fields recognized as damaged automatically (blue color) and manually (green color). Fields recognized as damaged by both methods are marked in brown. Red pixels describe the relative difference of NDVI.

4.3 Validation of Detected Damages by Experts

To check the accuracy of the visual "manual" method of identifying the fields as damaged, the obtained results were compared with the combat information provided by ACLED (Figure 8). For clarity, we selected the 8th observation period as a period of high biomass growth rates during summer vegetation.

As can be seen from Figure 8, the damage detected using the satellite monitoring method coincides with the official data on the attacked territories. Particularly damaged areas were found in the Donetsk and Herson region (Figure 8). Thus, the method makes it possible to estimate losses even in occupied territories.

On the graph in Figure 9 shows the distribution of the number of damaged fields by the distance from the official points of military shelling for the 8 period of hostilities.

As we can see, in a small radius from the combat zone, the percentage of damage is higher. More than half of the damaged fields are located in a 5-kilometer zone from the official shelling areas, and about a quarter - in a 10-kilometer zone. In addition, the severity of attacks can be retrospectively estimated from the indicators of detected damage. Therefore, according to our estimates, the most affected areas were recorded in the 9th period of the war (Jun - 3 Jul, 75.4% in a radius of up to 5 km) and 11 (18 Jul - 31 Jul, 64.6% in a radius of up to 5 km). As a result of all periods, total damage in Ukraine is 54.3%, 27.8%, 9.3%, 3.8%, 4.8% in radii up to 5 km, 10 km, 15 km, 20 km, respectively.

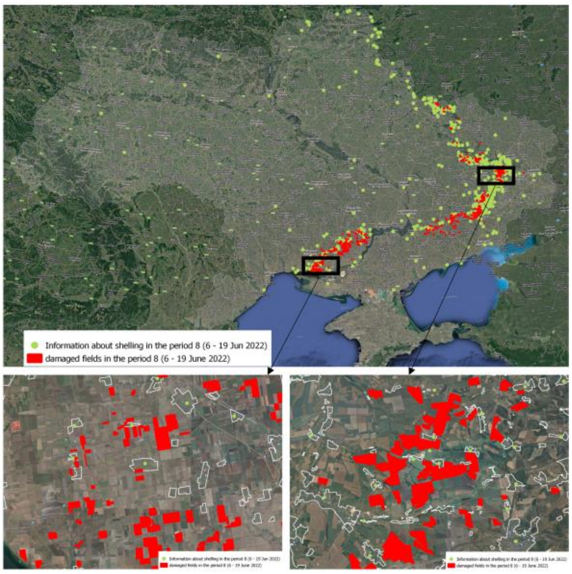

Figure 8: Geospatial location of identified damaged fields relative to official claims of military strikes for June 6-19, 2022. Examples of damages. Left - damaged fields Near Severodonetsk, Donetska oblast (June 6-19, 2022); Right - damaged fields near Herson city (June 6-19, 2022).

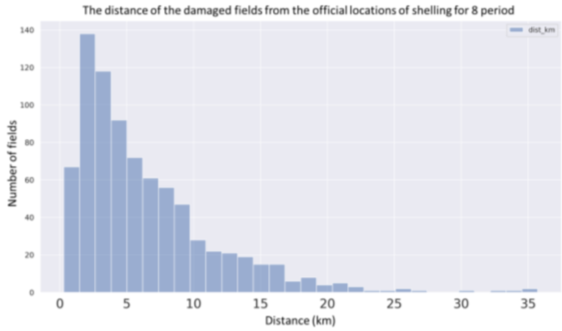

Figure 9: The distance of the damaged fields from the official locations of shelling for period 8 (June 6 – June 19, 2022).

5 CONCLUSIONS

As a result of this study, a method was developed for finding agricultural fields damaged as a result of military actions based on the relative difference of the NDVI index before and after active military actions in a specific territory and based of spectral channels. The method allows identification of point lesions of agricultural lands, such as explosions from bombs, traces of military equipment and the consequences of fires.

Damaged territories across Ukraine, including occupied lands, from the beginning of the armed conflict on February 24 to September 25, 2022, were identified. According to the results of the validation of the fields identified as damaged, it was established that the marked territories coincide with official data on the territories of military operations and are mostly located within a radius of up to 5-10 km from the zone of combat activities (up to 75.4% for the 9th period of the war, 20 Jun - 3 July). It was also found that Ukraine suffered the greatest area of damage during the 9th and 11th periods of the war (June-July).

As a next step it worth to test the proposed method for different stages of vegetation period and to discover informativeness of other indexes for detection the damages in the agricultural fields.

Thus, the method developed in this study to identify damage to agricultural fields due to war can be practically applied to help the government to accurately identify damaged land. This will provide an opportunity for the government of Ukraine and world representatives to correctly distribute financial resources among the affected landowners for the successful and effective restoration of the agricultural and industrial complex of Ukraine.

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