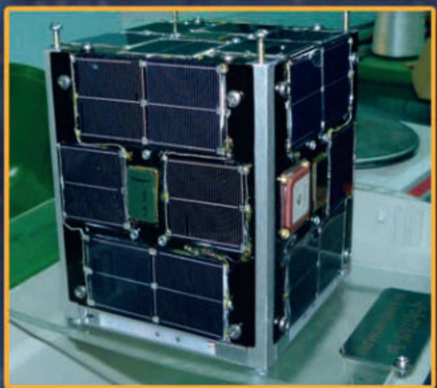
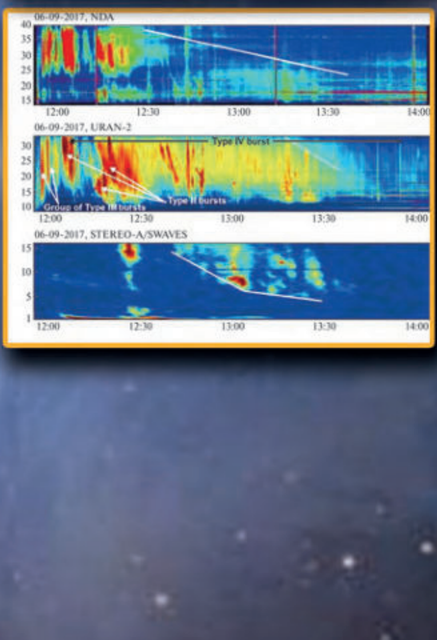
SPACE RESEARCH IN UKRAINE

2022–2024





NATIONAL ACADEMY OF SCIENCES OF UKRAINE

SPACE RESEARCH IN UKRAINE

2022—2024

**Report
to COSPAR**

*The Report Prepared by the Space Research Institute
of NAS of Ukraine and SSA of Ukraine*

Scientific Editor O. FEDOROV

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Report to COSPAR summarizes the results of space research performed during the years 2022—2024. This edition presents the current state of Ukrainian space science in the following areas: Space Astronomy and Astrophysics, Earth observation and Near-Earth Space Research, Life Sciences, Space Technologies and Materials Sciences. A number of papers are dedicated to the creation of scientific instruments for perspective space missions. Considerable attention paid to applied research of space monitoring of the Earth. The collection can be useful for a wide range of readers, interested in space research.

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CONTENTS

INNOVATIVE MODELS AND APPLICATIONS OF SATELLITE INTELLIGENCE

N. Kussul [1, 2, 3], A. Shelestov [1, 2], S. Drozd [1, 2], B. Yailymov [1], H. Yailymova [1, 2], M. Lavreniuk [1], L. Shumilo [3], S. Skakun [3]

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Introduction

The ongoing military conflict in Ukraine has had devastating impacts on the country's environmental monitoring [1], as well as agricultural lands, posing a severe threat to global food security [2]. Accurate and timely monitoring of crop production losses and field damages is crucial for guiding recovery policies, quantifying economic impacts, and ensuring food availability worldwide [3—21]. This study aims to leverage the power of satellite imagery and advanced machine learning techniques to address two critical tasks related to the war's effects on Ukrainian agriculture [22—30].

The first task focuses on developing an innovative data augmentation approach to enhance crop classification models' performance. Crop classification maps are vital for various agricultural applications, including yield estimation, risk assessment, and sustainable land management. However, the real-world distribution of crop types and land cover classes is often imbalanced, hindering the scalability and transferability of traditional machine learning models. To overcome this challenge, the study proposes a novel data augmentation method that employs Generative Adversarial Neural Networks (GANs) with pixel-to-pixel transformation [31—35]. This approach generates realistic synthetic satellite images and corresponding segmentation masks, capturing underrepresented crop type distributions and enabling better representation of minority classes during model training.

The second task addresses the quantification of war-induced crop losses in Ukraine and their impact on global food security [22—30]. By analyzing a multi-year panel of village councils across Ukraine, the study estimates the reduction in winter crop area and yield caused by the conflict. This analysis provides crucial insights into the direct and indirect effects of military activities on agricultural production, highlighting the need for targeted support and recovery efforts.

Furthermore, the study presents a robust methodology for near real-time monitoring and assessment of agricultural land damage caused by military actions [23—24]. Leveraging freely available Sentinel-2 satellite data, the proposed approach combines machine learning techniques with spectral band and vegetation index anomaly detection to accurately identify and delineate damaged fields. This automated monitoring system can aid in documenting war crimes, informing recovery analyses, and supporting targeted food security policies at local and global levels.

By addressing these critical tasks, this study aims to contribute to the advancement of satellite intelligence for agricultural monitoring, damage assessment, and the development of effective strategies to mitigate the severe consequences of armed conflicts on global food security. Since Ukraine is an associate member before joining Europe, currently active implementation of the Land Parcel Identification System practice has been initiated in Ukraine with the support of the World Bank.

The Training Data Imbalance Problem in Crop Classification

An efficient GAN architecture enables the generation of realistic synthetic satellite images for training data augmentation [31—36]. The relationship between satellite images and segmentation masks hinges on textural and multispectral features within the images. We trained a model capable of producing realistic satellite images for any artificially generated segmentation mask. This method allows for the creation of synthetic pairs of satellite images and masks, capturing unobservable crop type distributions and providing control over class balance in the dataset. We used 256 × 256 pixel sparse segmentation masks to generate 4-bands synthetic satellite images. The resulting augmentation algorithm shown on Fig. 1. First, we trained pix-2-pix GAN model to generate realistic satellite image based on the segmentation map. Then, we modified real segmentation maps to generate artificial masks with better representation of minority classes. After this, we combined original satellite data and generated into the joint training data collection that was used to train segmentation model with higher accuracy of minority classes separation [32, 33].

As a result, we created 2,384 synthetic satellite images with artificial masks using both GAN and statistical methods. We then trained four models: (I) using real satellite data; (II) combining real satellite data with synthetic images from the statistical method; (III) with synthetic images from the sampling method; (IV) with synthetic images from the GAN method. We applied standard augmentations like

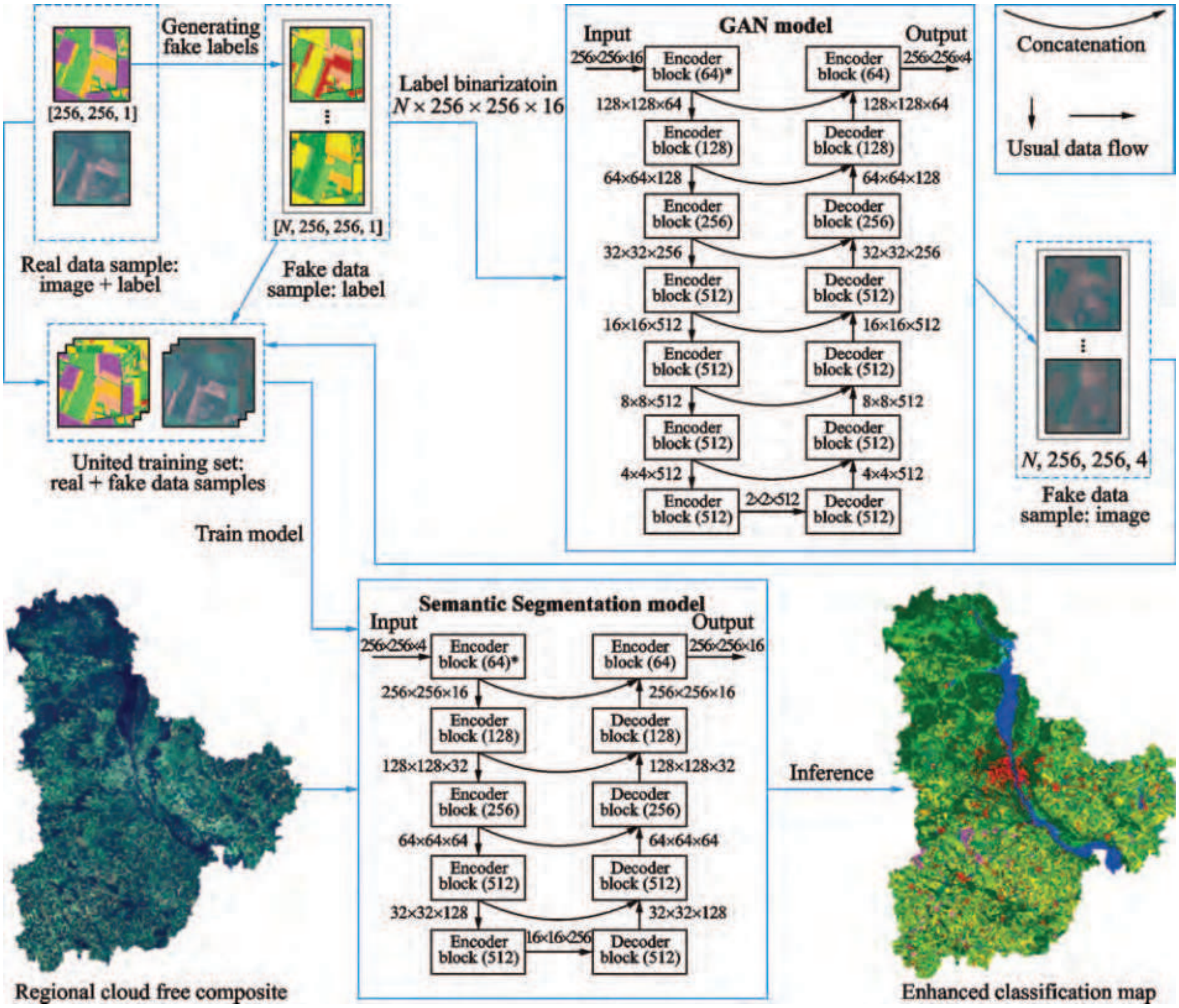

Fig. 1. Proposed GAN augmentation approach scheme for crop type mapping with use of deep learning segmentation model

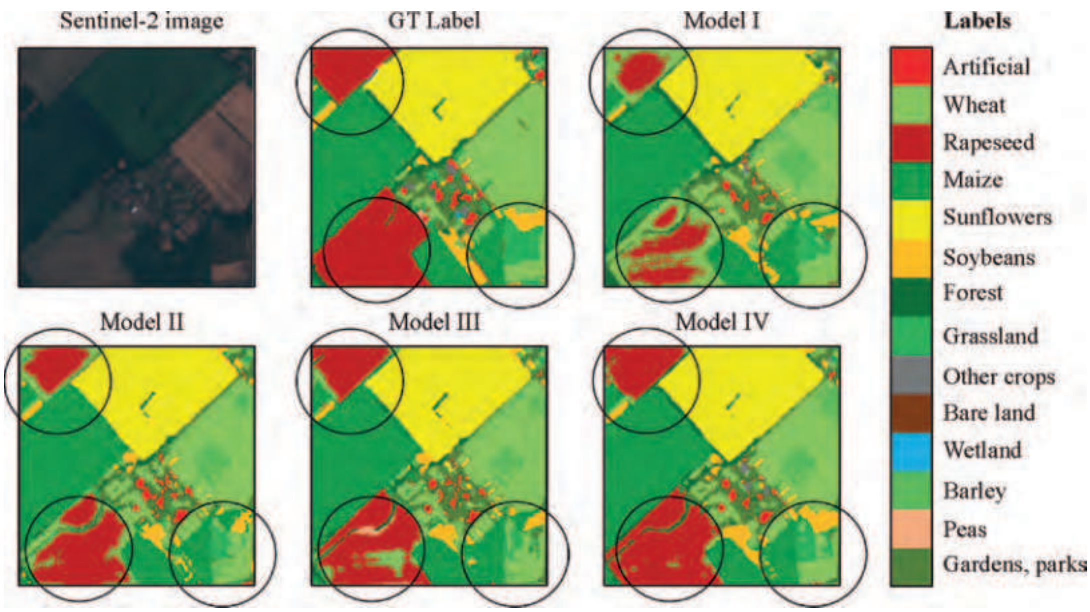

Fig. 2. Comparison of ground truth labels (GT Label) with classification results obtained using only real Sentinel-2 image (Model I), with generated by the statistical method data (Model II), with generated by the sampling method data (Model III), and with generated by the GAN method data (Model IV)

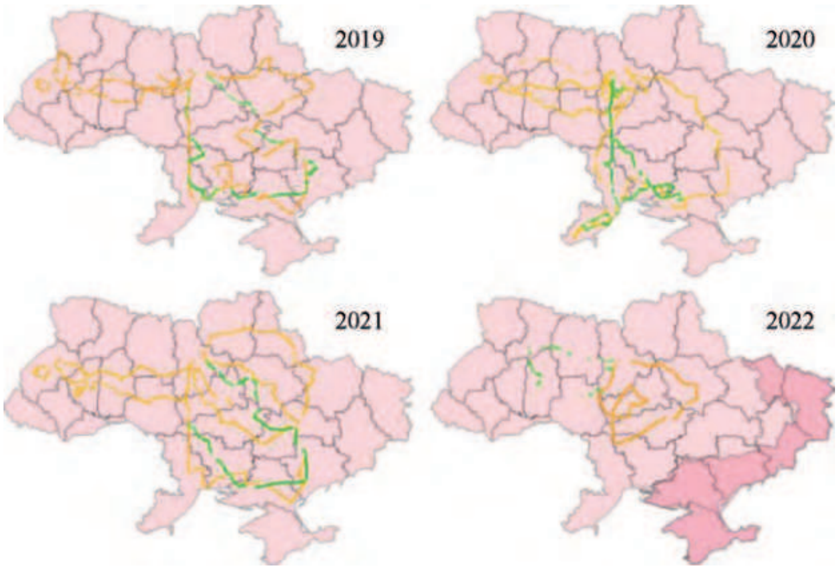

Fig. 3. Routes for in-situ training data collection, 2019—2022. Green and orange refer to the paths of ground data collection for winter and summer crops, respectively

rotations and flips and used the focal loss function to address class imbalance, incorporating established techniques. Subsequently, we evaluated the performance of these four methods on an independent testing dataset consisting of 2,125 real images. The model (I) achieved 77.3% Overall accuracy (OA) and 64.1% of Intersection over Union (IoU), however the average accuracies of cropland (AAC) for User Accuracy (UA), Producer Accuracy (PA) and IoU are very low, due to the high imbalance of real representation of crop classes. The model (IV), trained with use of proposed GAN augmentation methodology, overperformed model (I), model (II) and model (III). In comparison with model (II), average UA raised by 2.7%, PA by 1.1% and IoU by1.2%. In the same the OA accuracy and overall IoU increased by 1.4% and 1.6% relatively.

The Fig. 2 shows the visualization of obtained classification maps based on the models (I)—(IV). It is possible to mention that majoritarian classes like maize, wheat and sunflower have high quality on both maps. However, the minority class rapeseed (dark red) obtained by model (I) have defects and artefacts and much smaller quality in comparison with model (IV). This result can be explained precisely by the fact that GAN, unlike classical statistical methods of generation, allows retrieval of artificial examples that will preserve the similarity of not only the pointwise statistical characteristics of the classes, but also their textures.

The proposed new approach for the data augmentation in the task of crop classification is based on the GAN pix2pix model for realistic, in terms of multi-spectral and textural characteristics, image generation that provides the possibility to eliminate the problem of data set disbalance for deep learning semantic segmentation methods. The proposed method was compared with classical image generation approaches based on the statistical characteristics of multispectral features of crop type classes and has been tested upon basic augmentations and loss function applicable in a case of class imbalance. As a result, the proposed method outperformed models trained based on the real only data and classical approaches for most of cropland classes with significant improvement of accuracies for all minority classes.

Quantifying war-induced crop losses in Ukraine in near real time to strengthen local and global food security

While many studies investigate effects of conflict on food security, they focus on the demand rather than the supply side. To assess how the war is likely to affect Ukraine's production and thus global food security, we use Sentinel-2 imagery to construct outcome variables and indicators for the location and extent of conflict activity at different points in time. Although data used for winter crops, results point towards a reduction of up to 4.84 million tons of wheat only a small portion of which is attributable to direct field damages associated with the war and a reltively large effect on small farmers. This evidence already prompted several donors to establish cash transfers or investment grants targeted specifically at small farmers.

To provide training data for generation of crop cover estimates using machine learning techniques, in-situ data collection along main roads following JECAM guidelines was undertaken yearly from 2019 to 2021. In each year, two extended field trips, one for the winter and one for summer crops, were conducted (Fig. 3 presented the route maps in each year) [37—45].

Cloud-free satellite imagery from the period during which ground data were collected was then used to hand-label contiguous blocks of clearly identifiable crop cover that were used to train the machine learning model. While conflict conditions prevented in situ data collection during the spring, a ground survey for the 2022 crop was eventually organized in June 2022. Crop maps for 2019—21 build on analysis performed in [40, 41] who used optical data from Sentinel-2 and SAR data from Sentinel-1 during the vegetation period using a convolutional neural network

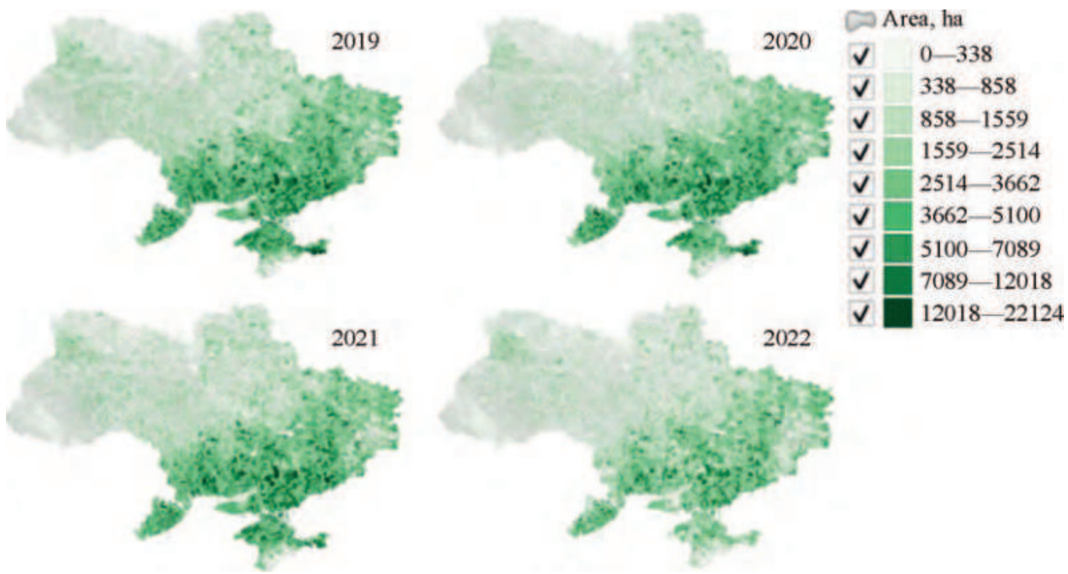

Fig. 4. Map of winter crop cover for 2019 to 2022 growing seasons

on the Amazon Web Services cloud computing platform as well as a random forests classifier on the Google Earth Engine (GEE) platform [46—49]. A winter crop mask for 2022 was created by computing the maximum NDVI for all of Ukraine in any two-week interval between February 1 to May 31 on GEE and applying threshold segmentation. Maps of the estimated winter cereal area by VC generated on this basis as displayed in Fig. 4 illustrate a concentration of winter cereals in the country's South and East and suggest a much lower level of winter cereal cover in 2022 and to some extent in 2020 than in 2021 and 2019.

We use a 4-year panel (2019—2022) of 10,125 village councils in Ukraine to estimate effects of the war started by Russia on area and expected yield of winter crops aggregated up from the field level. Satellite imagery is used to provide information on direct damage to agricultural fields; classify crop cover using machine learning; and compute the Normalized Difference Vegetation Index (NDVI) for winter cereal fields as a proxy for yield. Without conflict, winter crop area would have been 9.35 rather than 8.38 million ha, a 0.97 million ha reduction, only 14% of which can be attributed to direct conflict effects. The estimated drop associated with the conflict in NDVI for winter wheat, which is particularly pronounced for small farms, translates into an additional reduction of output by about 1.9 million tons for a total of 4.84 million tons. Taking area and yield reduction together suggests a war-induced loss of winter wheat output of up to 17% assuming the 2022 winter wheat crop was fully harvested.

Assessing Damage to Agricultural Fields from Military Actions in Ukraine

This study presents a robust methodology to automatically identify agricultural areas damaged by wartime ground activities using free Sentinel-2 satellite data [22]. The 10 meters resolution spectral bands and vegetation indices are leveraged, alongside their statistical metrics over time, as inputs to a Random Forest (RF) classifier. The algorithm efficiently pinpoints damaged fields, with accuracy metrics around 0.85. Subsequent anomaly detection delineates damages within the fields by combining spectral bands and indices. Applying the methodology over 22 biweekly periods in 2022, approximately 500 thousand ha of cropland across 10 regions of Ukraine were classified as damaged, with the most significant impacts occurring from March to September. The algorithm provides updated damage information despite cloud cover and vegetation shifts. The approach demonstrates the efficacy of automated satellite monitoring to assess agricultural impacts of military actions, supporting recovery analysis and documentation of war crimes.

The algorithm identifies direct damages on the fields as anomalies in Sentinel-2 images. The algorithm is structured into three primary steps, as illustrated in the level-0 dataflow diagram in Fig. 5:

1. Experts manually identify damaged fields to create training and test datasets.
2. The machine learning model, specifically RF classification, is employed to recognize damaged fields.
3. Damaged areas within these fields are further identified using threshold segmentation for anomaly detection.

According to satellite bands and vegetation indexes analysis the B2 (Blue) and B3 (Green) spectral bands are especially effective for pinpointing damage in fields with sparse vegetation. On the other hand, vegetation indexes NDVI and GCI are more efficient at detecting damage in fields with dense vegetation. As a Machine Learning model, we have chosen the RF classifier with binary output, classifying fields as either damaged or undamaged. The inputs for this model will be the statistical attributes of the most pertinent spectral bands and vegetation indices. To evaluate the accuracy of the model efficacy, we use widely accepted metrics, including user's accuracy (precision), producer's accuracy (recall), and the F1-score.

To ensure the validity of the experiment, considering vegetation shifts, we construct distinct classification models for each study period. We adopt the 5-fold cross-

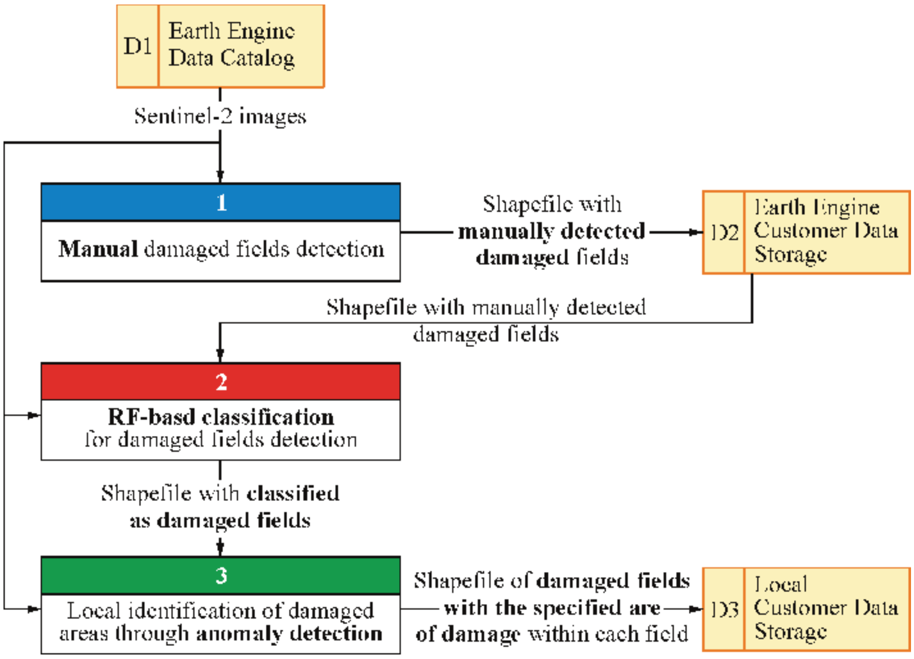

Fig. 5. Level-0 Dataflow Diagram for Damage Detection

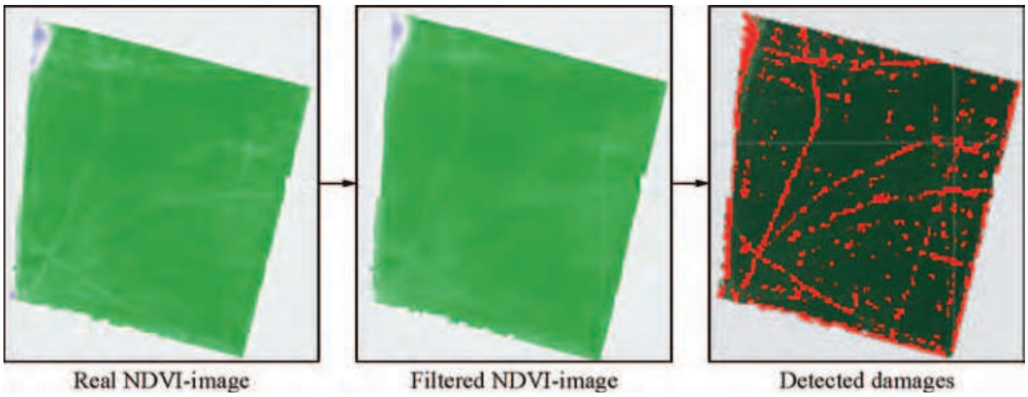

Fig. 6. Damages identification using vegetation indexes filtering

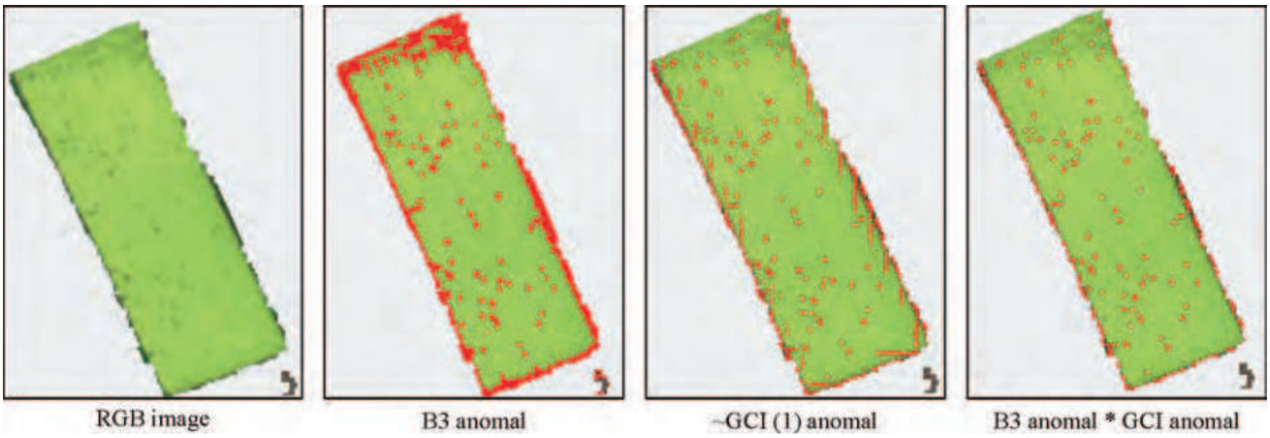

Fig. 7. Damage detection using the Green band B3 and the GCI index, NDVI = 0.63 < 0.65, May 9—23, Zaporizhzhia region

validation method (allocating 80% for training and 20% for validation). During this process, we evaluate accuracy metrics for each iteration and compute their mean, providing accuracy estimates for each period. Finally, we aggregate these metrics across periods to determine the overall classification accuracy.

To detect anomalies with vegetation indices we implement smoothing, applying a 5 × 5 mean filter to the raster

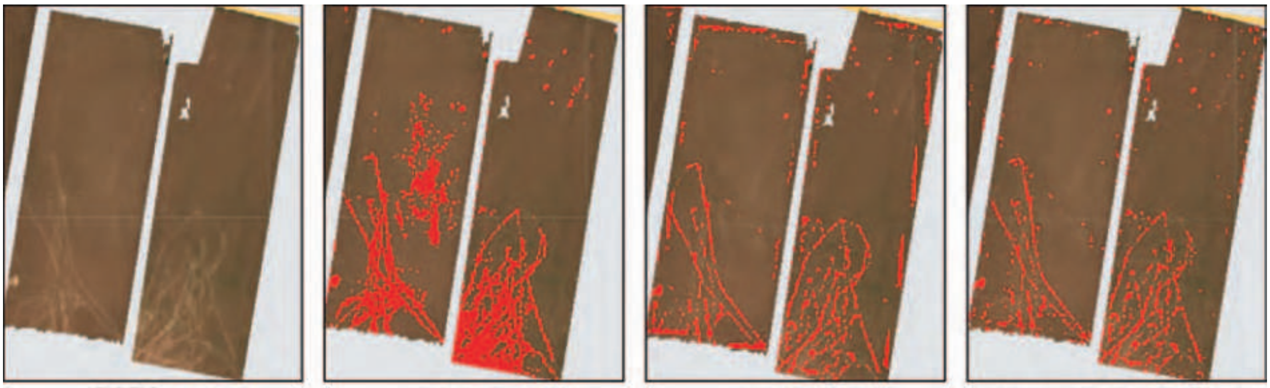

Fig. 8. Damage detection using the Blue band B2 and the GCI index, NDVI = 0.43 < 0.65, June 20 — July 4, Zaporizhzhia region

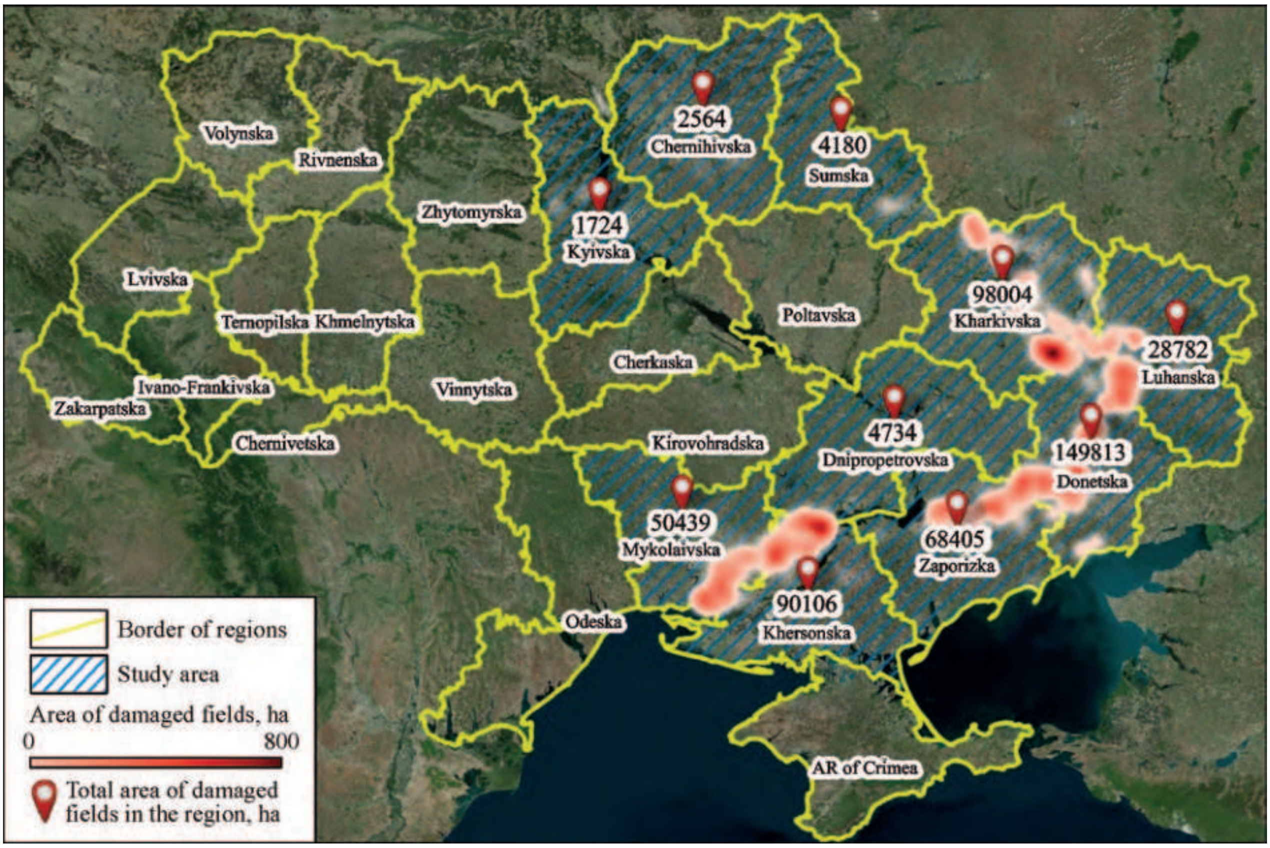

Fig. 9. Heat map of damaged agricultural fields and total areas of damage by region

maps of the vegetation indices. Then we compute the difference between the actual vegetation index values and the smoothed values at each pixel. This differential analysis aids in spotting anomalies or deviations, signaling potential field damage. Fig. 6 illustrates the results of the proposed algorithm.

Similarly, the concurrent anomalies in the GCI index and the Blue band B2 facilitate the identification of craters from bomb detonations on both highly and sparse vegetated fields. To delineate these damages, we intersect anomalous pixels from GCI and B2 (for NDVI < 0.65, Fig. 7). Concurrent anomalies in the inverse GCI index and the Green band B3 help to identify anomalies with moderate to low vegetation (NDVI < 0.65, Fig. 8).

We run RF classification models for each region and for every individual 2-weeks period separately (started from 24 February, 2022). Then we calculated the accuracy metrics for these models and averaged the results by region and by period. The period-wise results demonstrate relatively consistent accuracy levels across the board.

The analysis by regions reveals that the most significant damage occurred in the Donetsk region, where approximately 149 th. ha or 30% of the total damaged agricultural area were affected by the war. Following that, the Kharkiv region experienced damage to approximately 98 th. ha (19.65%). The Kherson and Zaporizhzhia regions recorded damages on 90 th. ha (18.1%) and 68 th. ha (13.72%) respectively (Fig. 9).

Overall, considering all regions over the entire evaluation duration, the war has impacted a cumulative area of 499 th. ha of agricultural land.

This work presents a robust methodology to automatically identify approximately 500,000 ha of cropland damaged by wartime ground activities across 10 regions of Ukraine using free Sentinel-2 satellite data. The 10 meters resolution spectral bands and vegetation indices are leveraged, alongside their statistical metrics over time, as inputs to a RF classifier.

The algorithm efficiently pinpoints damaged fields, with producer and user accuracy metrics consistently around 0.85. Subsequent anomaly detection combining spectral bands and indices delineates localized damages within the fields. The approach is applied over 22 biweekly periods in 2022, revealing heightened impacts from March to September.

Conclusions

This study presents an innovative approach to near real-time monitoring of agricultural land damage caused by military activities in Ukraine, utilizing freely available Sentinel-2 satellite data and advanced machine learning techniques. The proposed methodology effectively addresses several critical challenges, including the imbalanced distribution of crop types and land cover classes in real-world data, which hinders the scalability and transferability of traditional classification models.

To overcome the data imbalance problem, a novel data augmentation method employing Generative Adversarial Neural Networks (GANs) with pixel-to-pixel transformation (pix2pix) is introduced. This approach generates realistic synthetic satellite images and corresponding segmentation masks, capturing unobservable crop type distributions and enabling better representation of minority classes during model training. The GAN-based augmentation technique outperformed classical statistical methods, significantly improving the accuracy of crop classification, particularly for minority classes.

Furthermore, the study quantifies the war-induced crop losses in Ukraine, highlighting the severe impact on global food security. By analyzing a 4-year panel (2019—2022) of village councils across Ukraine, the study estimates a reduction of up to 4.84 million tons of winter wheat output, representing a staggering 17% decrease. This loss is attributed not only to direct field damages but also to the indirect effects of the conflict on small farmers, emphasizing the need for targeted support and recovery policies.

The proposed damage detection algorithm, which combines machine learning techniques with spectral band and vegetation index anomaly detection, has proven highly effective in identifying and delineating damaged agricultural fields. With overall accuracy metrics consistently around 0.85, the algorithm has successfully identified approximately 500,000 hectares of cropland damaged across 10 regions of Ukraine during the 2022 growing season.

The study's findings underscore the critical importance of near real-time monitoring and assessment of agricultural land damage during armed conflicts. The developed methodology can aid in documenting war crimes, quantifying production losses, and informing targeted recovery efforts and food security policies at both local and global levels.

In conclusion, this research contributes significantly to the advancement of satellite intelligence for agricultural monitoring and damage assessment, while also highlighting the pressing need for international cooperation and support to mitigate the severe consequences of the ongoing conflict on global food security.

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