



Contents lists available at ScienceDirect

International Journal of Applied Earth Observation and Geoinformation

journal homepage: www.elsevier.com/locate/jag

Assessment of war-induced agricultural land use changes in Ukraine using machine learning applied to Sentinel satellite data

Nataliia Kussul^{a,b,c,*}, Andrii Shelestov^{b,c}, Bohdan Yailymov^c, Hanna Yailymova^{b,c}, Guido Lemoine^d, Klaus Deininger^e

^a University of Maryland, College Park, MD 20742, United States

^b National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute", Beresteyskiy ave 37, 03056 Kyiv, Ukraine

^c Space Research Institute NASU-SSAU, Glushkov ave 40, 4/1, 03187 Kyiv, Ukraine

^d Joint Research Center of the European Commission, Ispra, Italy

^e The World Bank, 1818 H Street NW, Washington, DC, United States

ARTICLE INFO

Keywords:

Agricultural land use change
War impact
Cropland
Uncultivated lands
Ukraine
Google Earth Engine
Copernicus Data Space Ecosystem
Sentinels
Machine learning

ABSTRACT

The ongoing war in Ukraine has significantly disrupted agricultural land use, leading to reduced cropland areas, increased land abandonment, and heightened uncertainty in food production. This study presents a multi-year assessment of war-induced agricultural land use changes in Ukraine using machine learning-based classification applied to Sentinel-1 and Sentinel-2 satellite imagery. By leveraging cloud computing platforms, including Google Earth Engine (GEE) and the Copernicus Data Space Ecosystem (CDSE), we develop high-resolution KPI-Ukraine (Igor Sikorsky Kyiv Polytechnic Institute (KPI) in Ukraine) land use maps spanning from 2016 to 2024. The study integrates Random Forest and Multi-Layer Perceptron classification techniques to improve accuracy, addressing spectral ambiguities and classification noise. Additionally, a novel transfer learning approach enables reliable classification in conflict-affected areas with limited ground-truth data.

We achieved high classification accuracy across the 14 major crop types in Ukraine and abandoned land, validated through F1-scores exceeding 90 % for most classes. The fusion of the results generated on the GEE and CDSE platforms enhanced the classification accuracy for minor classes. Our analysis reveals significant reductions in cultivated land in 2022–2024, particularly in conflict zones, where agricultural activity has been heavily disrupted. Overall, Ukraine's arable land area shrunk by 10 % nationwide. The consistently high accuracy of our classification methodology across the nine-year study period demonstrates its robustness and suitability for long-term monitoring of agricultural dynamics in conflict-affected regions and provides a valuable tool for guiding post-war recovery efforts. Our findings underscore the importance of leveraging satellite data for timely and accurate land use monitoring, supporting policymakers in addressing food security challenges and promoting sustainable agricultural practices. This framework also holds potential for broader applications in monitoring land use changes in conflict zones and regions undergoing rapid environmental shifts.

1. Introduction

Ukraine plays a significant role in global agricultural production, particularly in the export of grains and oilseeds (Welsh and Dodd, 2022), as well as it is in the top five exporters of wheat, maize, and barley globally (Dodd et al., 2024; Ben Hassen and El Bilali, 2022; World economic forum, 2024).

However, the ongoing war in Ukraine has disrupted agricultural

production with approximately 10 % reduction in cultivated areas (Deininger et al., 2023; Kussul et al., 2022) and 500,000 ha of arable land in 2022 (Kussul et al., 2023a). To offset the loss of Ukrainian wheat exports, wheat grain yields will need to increase by at least 8 % (Júnior et al., 2022).

Recent studies highlight Ukraine's **critical** role in global food security, with Lin et al. (2023), Glauber and Laborde Debucquet (2023), and USDA (2024) reports projecting severe war impacts including harvest

* Corresponding author.

E-mail addresses: kussul@umd.edu (N. Kussul), andrii.shelestov@gmail.com, andrii.shelestov@lll.kpi.ua (A. Shelestov), yailymov@gmail.com, yailymov@ikd.kiev.ua (B. Yailymov), anna.yailymova@gmail.com, yailymova.hanna@lll.kpi.ua (H. Yailymova), guido.lemoine@ec.europa.eu (G. Lemoine), kdeininger@worldbank.org (K. Deininger).

<https://doi.org/10.1016/j.jag.2025.104551>

Received 28 October 2024; Received in revised form 15 April 2025; Accepted 18 April 2025

Available online 8 May 2025

1569-8432/© 2025 The Author(s). Published by Elsevier B.V. This is an open access article under the CC BY-NC license (<http://creativecommons.org/licenses/by-nc/4.0/>).

reductions and price increases (Ihle et al., 2022; Countryman et al., 2024; Leal Filho et al., 2023; Devadoss and Ridley, 2024) alongside Russia's control of key agricultural regions (Welsh and Glauber, 2024). Ukraine's economic losses stem from widespread land use changes including agricultural abandonment (Dai et al., 2024; He et al., 2023), reduced cultivation (Ma et al., 2022; Li and Song, 2023), deforestation (Matsala et al., 2025), and ecosystem degradation (Chai et al., 2024; Solokha et al., 2023; Pereira et al., 2022a), causing cascading impacts on ecosystems (Hartman et al., 2024), food security (Ben Hassen and El Bilali, 2022; Leal Filho et al., 2023), and sustainable development (Pereira et al., 2022b).

During the ongoing war in Ukraine, the government and international organizations lack objective and up-to-date statistical information about land use, particularly in areas directly affected by military operations. Direct access to these territories is severely restricted due to safety concerns and operational challenges. Earth Observation (EO) data, especially from the **Copernicus Sentinel-1 and Sentinel-2 satellites**, is critical for tracking war-related land use changes in Ukraine. With 10 m spatial resolution, these freely available datasets enable accurate crop classification and area estimation. Sentinel data supports real-time monitoring of agricultural land use, offering decision-makers up-to-date insights during conflict (Copernicus, 2021).

The analysis of land use changes in Ukraine relies on land cover maps with various agricultural crops. While several global maps exist (see Table 1s), they use low-resolution sensors (100–500 m), lack coverage for 2021–2024, and only include general “cropland” categories with inconsistent definitions. The Global Land Analysis and Discovery (GLAD) team provides 30 m resolution land use change data from 2000 to 2020 (Potapov et al., 2022; Potapov et al., 2020), while the ESA's World Cereal project offers 10 m resolution crop-specific mapping for Ukraine for 2021 (Van et al., 2023).

A lot of studies for analysis agricultural land use and the war's impact on land use in Ukraine using satellite data has significantly intensified with the start of hostilities in 2014 and the start of a full-scale invasion in 2022. Most of them examine changes for land cover classes only, usually forest or cropland. Shumilo et al. (2023) and Skakun et al. (2022) analyzed the ecological impact of military operations on forests. They found significant forest damage within the Emerald Network in the occupied territories starting from 2014. The negative impact on forest areas during the full-scale invasion since 2022 has been studied by Matsala et al. (2024), Matsala et al. (2025), and Myroniuk et al. (2024). Skakun et al. (2019) analyze significant changes in cropland and abandoned cropland in the occupied territories after the Russian invasion in 2014 by frontline regions. This work does not cover the full-scale invasion period. He et al. (2023), Dai et al. (2024), Ma et al. (2022), Kussul et al. (2022), Chen et al. (2024) analyzed cropland changes in 2022 after a full-scale invasion.

Skakun et al. (2022) analyzed changes in sunflower cultivation following the full-scale invasion using Sentinel-1 radar data, as well as Qadir et al. (2024) used Random Forest (RF) based model using Sentinel-1 satellite data. Chen et al. (2024) assessed the impact of the war on planted areas by NDVI analyzes during 2019–2022 for 5 oblasts of Ukraine: AR Crimea, Donetsk, Kherson, Luhansk and Zaporizhia, He et al. (2023) analyzed 2020–2022 for Kherson, Zaporizhia, Dnipropetrovsk, Donetsk, Luhansk and Kharkiv oblasts, as well as Dai et al. (2024) detected abandoned land for all Ukraine in 2022. All these authors used a single WorldCover 2020 to identify agricultural lands. Also, territories abandoned as a result of the war were analyzed by Ma et al. (2022) using two consecutive cropland maps based on Random Forest classifiers over two years and detected NDVI changes.

During wartime, limited access to territories for collecting ground data creates challenges in developing land cover maps. Lin et al. (2023) addressed this by generating custom training datasets based on existing global products, while Ma et al. (2022) combined these datasets with expert knowledge in image interpretation. However, some crops can be identified using spectral characteristics and growth stage information.

Skakun et al. (2022) analyzed changes in sunflower cultivation following the full-scale invasion using Sentinel-1 radar data. Similarly, Lin et al. (2023) examined wheat losses across Ukraine using European land cover maps (d'Andrimont et al., 2021). Chen et al. (2024) assessed the impact of the war on areas planted with wheat, maize, sunflower, and rapeseed using spectral indices. Wagner et al. (2023) combined expert knowledge with remote sensing to evaluate changes in winter cereal, rapeseed, and summer crop areas, as well as increases in fallow land after the invasion. Rosa et al. (2024) developed crop-specific maps for 2017–2022 using an existing 2019 map (Kussul et al., 2020), but their analysis was limited to irrigated areas and did not evaluate national-level trends in crop area changes. Deininger et al. (2023) examined declines in winter crop productivity after the invasion using crop-specific maps from 2019 to 2022 (Kussul et al., 2020). All these regional studies are limited in scope, focusing on either a single crop or total cropland, relying on a narrow selection of source data (only a few products covering Ukraine), and lacking sufficient in-situ data for quality assessment.

Thus, existing studies primarily analyze the impact of the war on cropland areas or specific crops during 2022. To date, there are no known studies that systematically investigate the wide variety of agricultural crops grown in Ukraine or examine changes in crop areas over both the pre-war period and multiple years of the conflict.

The literature review indicates that the ability to comprehensively analyze the dynamics of crop area changes by type is limited by the lack of ground-based observations. Consequently, most studies rely on a single land cover map, typically from 2020 or 2021, predating the full-scale invasion (Qadir et al., 2024; Skakun et al., 2022; Dai et al., 2024; He et al., 2023; Kussul et al., 2022). Other studies create custom maps based on data from 3–4 years prior to the invasion (Lin et al., 2023; Ma et al., 2022; Chen et al., 2024; Rosa et al., 2024) without utilizing real in-situ data or fail to compare results with pre-war years altogether (Wagner et al., 2023).

Over the past decade, our team has continuously advanced a crop classification methodology that integrates state-of-the-art remote sensing and machine learning techniques. Initially proposed by Kussul et al. (2017), the method was later refined by Shelestov et al. (2020) by integrating Sentinel-1 and Sentinel-2 data and utilizing deep learning techniques. The resulting crop classification maps for the 2016–2018 period achieved high accuracies and provided detailed information on the spatial distribution of major crops in Ukraine. This methodology was further developed by the team at the National Technical University of Ukraine “Igor Sikorsky Kyiv Polytechnic Institute (NTUU “KPI”) and became fully operational, enabling the delivery of crop-specific maps for Ukraine starting in 2016. The in-situ data collection and crop map deliveries were supported by the World Bank and the EU's “Supporting Transparent Land Governance in Ukraine” program, funded by the EU (Kussul et al., 2016, 2018; Kussul et al., 2019). Maps based on this methodology have been delivered annually from 2016 to the present (2024). Currently, it remains the only consistent tool for long-term monitoring of land use changes in Ukraine, particularly in the context of the ongoing war and reconstruction efforts. The following sections will discuss the validation of existing products, provide an overview of the developed methodology, compare the available products with the maps generated by our approach, and present a nine-year trend analysis of land use changes in Ukraine.

So, existing studies primarily focus on analyzing land use changes in Ukraine for **croplands** or **some specific crops** during the initial year of the full-scale invasion in 2022. These studies typically **lack in-situ data** or are based on limited access to ground observations, which restricts their scope and precision.

Therefore, the **research gap** lies in the **absence of systematic, multi-year analyses** of agricultural land use changes **across a wide variety of crop types in Ukraine** during both the pre-war period and the years of the ongoing full-scale invasion (2022–2024). Existing studies predominantly focus on single land cover classes (e.g., forests or

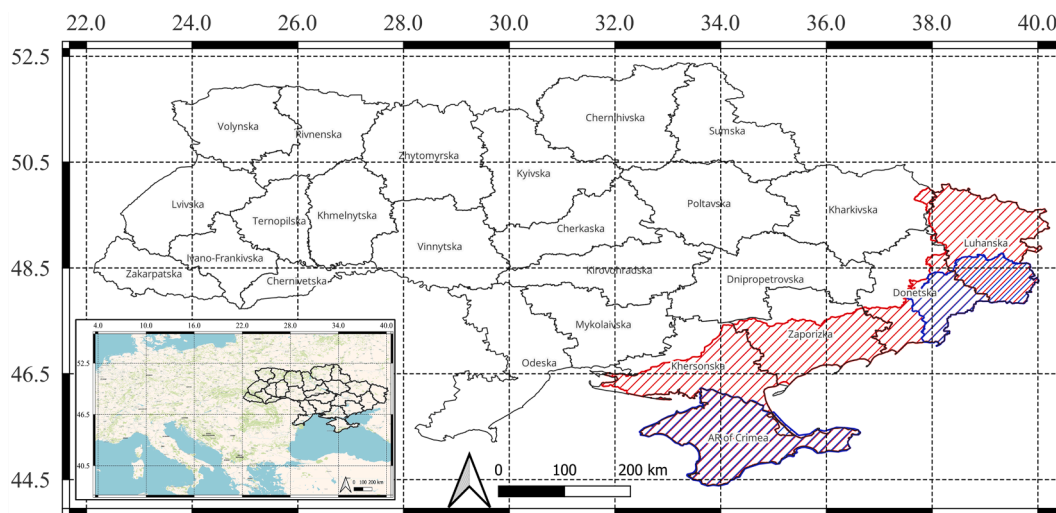


Fig. 1. Geographic Location of Ukraine. Red dashed lines indicate the territories occupied as of 2024 since 2022, while blue areas represent territories occupied by Russia since 2014. The names of the regional units (Oblasts) are used throughout the text. The inset shows the broader context of Ukraine’s location within Europe. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

croplands) or specific crops during the initial year of the full-scale invasion (2022), often relying on limited or outdated datasets without sufficient validation through in-situ observations. This gap hinders the understanding of broader trends and long-term impacts of the war on agricultural land use, as well as the ability to accurately assess and address these changes or make informed decisions for post-war recovery.

During the war, access to certain territories for ground data collection became severely restricted, making traditional methods of land use classification unavailable. This situation necessitates the development of robust methods for land use and land cover classification that can function effectively under crisis conditions, with limited access to in-situ data, statistical information, and computational resources. To address this research gap and overcome these challenges, in this paper, we are going to address the following **research questions**:

1. How to ensure reliable land use and crop classification in conditions of limited access to territories at the national level?
2. What are the hotspots of the LCLU changes and transitions between LULC in Ukraine due to the ongoing war?

The first question addresses the need for innovative methodologies that do not rely solely on traditional in-situ data collection and instead leverage transfer learning, and robust data fusion techniques. The second question focuses on identifying the regions where the most significant land use and crop variety changes are occurring as a direct or indirect result of the war. Understanding these hotspots is critical for prioritizing resources, planning recovery efforts, and mitigating further environmental or agricultural impacts.

By addressing these research questions, this study aims to fill the identified gaps in the current literature, providing a multi-year analysis of agricultural land use changes in Ukraine during the ongoing war. This paper introduces robust methodology and a framework for analyzing agricultural land use changes in Ukraine by leveraging advanced cloud computing platforms, high-resolution satellite data, and machine learning algorithms. We produce a unique time-series dataset of 10-meter resolution annual land use maps generated using Sentinel-1 and Sentinel-2 data. By employing machine learning techniques like Random Forest and neural networks, we achieve high classification accuracy, with extensive field validation ensuring reliability. The methodology allows long-term monitoring of trends in agricultural land use in Ukraine from 2016 to 2024.

The structure of the paper is organized as follows. In the next [Section](#)

2, we show the study area and in-situ data used for training machine learning models and accuracy assessment of the produced maps. The methodology of our land cover/land use mapping, leveraging the Copernicus Data Space Ecosystem (CDSE) and Google Earth Engine (GEE) platforms, is discussed in [Section 3](#), including the classification algorithms and processing steps. In [Section 4](#), we validate the accuracy of our products obtained on two different cloud platforms and their combination, comparing them with other available regional maps, and present accuracy assessments for various crops and land use classes. In [Section 5](#), we analyze trends in land use change, particularly in the context of the war’s impact on Ukraine’s agricultural sector. [Section 6](#) discusses the findings and limitations of the methodology, as well as potential directions for future development. Finally, [Section 7](#) provides concluding remarks, highlighting the importance of this methodology in guiding post-war reconstruction and promoting sustainable land management strategies.

2. Study area and in-situ data

2.1. Study area

The area of interest in this study is Ukraine, the largest country in Europe, covering approximately 603,550 km². Geographically, Ukraine is located in Eastern Europe, between latitudes 44° and 53° N and longitudes 22° and 41° E. The climate is predominantly temperate continental, creating favorable conditions for agriculture. Ukraine is one of the world’s leading producers of agricultural products, particularly grains, oilseeds, and sunflower oil.

Ukraine’s agricultural landscape is characterized by vast plains and highly fertile black “chernozem” soil, covering approximately 43 Mha. Winter crops (winter wheat, winter barley and rapeseed) are sown in the early fall (September–October), hibernate over the winter period and are harvested in the June–July period. Spring planting starts in March (spring barley, other spring cereals) and will last until May (maize, sunflower, soybean) with harvests in the August–October period. Exact timing of sowing and harvest activities follow the agro-meteorological trends in accumulated temperature (growing degree days) that increases along the North-East to South-West direction and may depend on seasonal soil moisture status. Since 2014, Ukraine has faced military conflict in the eastern part of the country, and on February 24, 2022, Russia’s full-scale invasion further disrupted agricultural activities, particularly in the occupied territories ([Fig. 1](#)). Over 100,000 km² of land has been impacted, making access to these areas difficult or

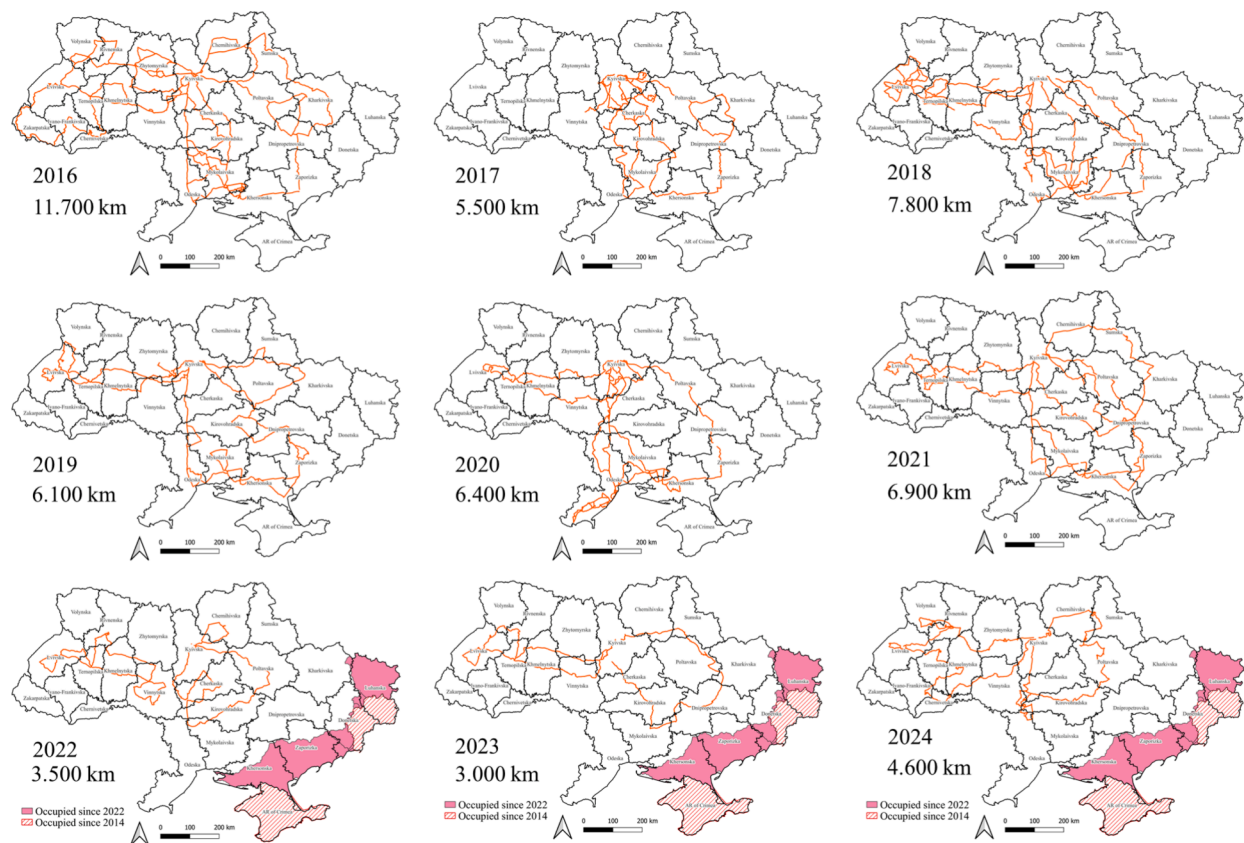


Fig. 2. Geographical location of collected data during ground survey along the roads throughout Ukraine for 2016 – 2024 (orange line). The total distance of surveyed routes, measured in kilometers, is highlighted for each year. Occupied areas are indicated on the maps: regions marked in pink represent territories occupied since 2022, while lighter pink denotes areas under occupation since 2014. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

impossible. The conflict has significantly hindered data collection efforts, including the ability to gather accurate statistics on agricultural land use. As a result, the area available for in-situ data collection has been reduced, making remote sensing technologies essential for monitoring land use changes and agricultural productivity.

2.2. Description of in-situ data used for validation

Crop classification is an application of supervised machine learning. Since 2016, in-situ data, which serves as class labels for the development of land cover and crop-specific maps in Ukraine, has been gathered annually along roadways. In this paper the data also is used to validate global LC/LU products for the territory of Ukraine. The data collection occurs through two expeditions each year: one in April-May targeting winter crops and another in June focusing on summer crops. Annually, around 10,000 samples are collected representing various crop types. The ground data collection along roads in Ukraine has been carried out as part of the World Bank and EU initiative “Supporting Transparent Land Governance in Ukraine,” as well as the EU-funded project “Support to Agriculture and Food Policy Implementation (SAFPI)” (Shelestov et al., 2021).

In-situ data collection is performed along the roads according to the JECAM guidelines for cropland and crop type definition and field data collection (JECAM Guidelines; Kussul et al., 2014). Roadside data collection, as demonstrated in the study (Waldner et al., 2019), proves to be a viable method for in situ data collection in cropland mapping, including crop-specific classification tasks. In-situ information about crop types is collected with Avenza software (Avenza, 2024). We select the regional roads instead of highways to be able to stop and inspect the crop on the field if it is not visible from the car. After the ground survey

the dataset is created in the office by an GIS expert, who digitizes the polygons for the field corresponding to the GIS coordinates of collected points. The location of the polygons is determined using the recent Sentinel-2 data to ensure that the polygons cover a single parcel.

Fig. 2 shows the routes used for data collection on winter and summer crops each year from 2016 to 2024. These routes were designed to cover the entirety of Ukraine, ensuring a representative sampling of the country’s agricultural landscape. However, following the full-scale invasion in 2022, both the length of the routes and the number of collected samples decreased significantly due to restricted access and safety concerns in certain regions. The length of the routes and the number of polygons used for model training and testing varied each year, with route distances ranging from 11,700 km in 2016 to just 3,000 km in 2023. In 2024, thanks to additional project activities, the number of collected samples increased again. The areas shaded in light pink in Fig. 2 represent territories occupied by Russia since 2014, while the darker pink highlights areas occupied after the full-scale invasion.

Despite the limitations due to the conflict situation in the period 2022–2024, the teams have maintained extensive coverage, capturing data on 14 agricultural classes as well as the war-specific category “uncultivated land”.

The collected in-situ data was divided into training (TR) and testing (TT) (validation – VAL) subsets. The training data was used to train the model and generate classification maps, while the test data validated both the classification maps and global Land Use Land Cover (LULC) maps. From 2016 to 2020, the data was split evenly (50:50), but from 2021 to 2024, the split was adjusted to 80:20 in favor of training data. This adjustment was made as the technology matured—initially, more data was allocated to independent testing to ensure map quality, but as the methodology advanced and confidence in the technology grew,

Table 1

The route length and number of polygons, used for the model training (TR) and testing (TT) crop classification maps for 2016–2024.

Route length (km) Percentage of TR/TT (%)	2016		2017		2018		2019		2020		2021		2022		2023		2024	
	50 %/50 %		50 %/50 %		50 %/50 %		50 %/50 %		50 %/50 %		80 %/20 %		80 %/20 %		80 %/20 %		80 %/20 %	
	TR	TT	TR	TT	TR	TT	TR	TT	TR	TT	TR	TT	TR	TT	TR	TT	TR	TT
Wheat/Cereal	933	931	586	586	1146	1146	1797	1776	1320	1313	2286	562	950	250	796	192	1262	309
Barley	198	197							591	583	701	164	199	45	183	39	308	68
Rapeseed	94	94	107	106	196	195	288	278	273	265	390	92	244	47	266	63	277	62
Buckwheat	16	16					13	10	32	29	64	12	65	14	62	12	37	5
Maize	514	513	344	344	486	486	576	566	855	850	1469	360	990	275	587	140	1060	261
Sugar beet	30	29	20	19	69	69	36	29	36	30	66	12	42	7	65	10	62	10
Sunflower	823	822	596	595	876	875	690	681	794	790	1594	391	932	262	683	161	921	221
Soybeans	273	272	191	190	325	324	373	367	389	382	660	158	627	165	547	131	1795	441
Peas	16	16	25	24	38	38	37	34	61	55	108	18	40	2	10	2	39	6
Alfalfa	26	26					45	34	38	31	89	13	32	3	27	3	102	18
Potato	9	8									106	21	18	4	24	5	83	12
Grape							231	224	249	248	279	67	261	62	340	81	367	89
Low trees	43	43					191	176	208	197	283	59	292	63	245	56	386	74
Other crops	51	49			104	104	113	108	123	117	178	12	48	7	35	1	132	18
Total crops	3026	3016	1869	1864	3240	3237	4390	4283	4969	4890	8273	1941	4740	1206	3870	896	6831	1594
Artificial	68	67	68	67	164	164	222	223	244	237	442	103	444	123	567	131	583	131
Forest	338	338	342	341	666	665	223	224	297	291	664	151	818	194	769	165	812	160
Grassland	399	399	272	272	651	650	888	866	965	957	1662	403	1670	397	1427	343	1549	371
Bare land	57	57	54	54	81	80	135	115	138	122	202	41	200	41	242	50	254	52
Water	88	88	96	96	240	240	351	327	350	340	600	138	600	140	623	145	642	141
Wetland	24	24	35	35	66	66	107	114	133	119	297	64	296	67	357	76	367	76
Damaged forest															204	50	244	59
Uncultivated lands															206	48	249	61
Total non-crops	974	973	867	865	1868	1865	1926	1869	2127	2066	3867	900	4028	962	4395	1008	4700	1051
Total	4000	3989	2736	2729	5108	5102	6316	6152	7096	6956	12,140	2841	8768	2168	8265	1904	11,531	2645

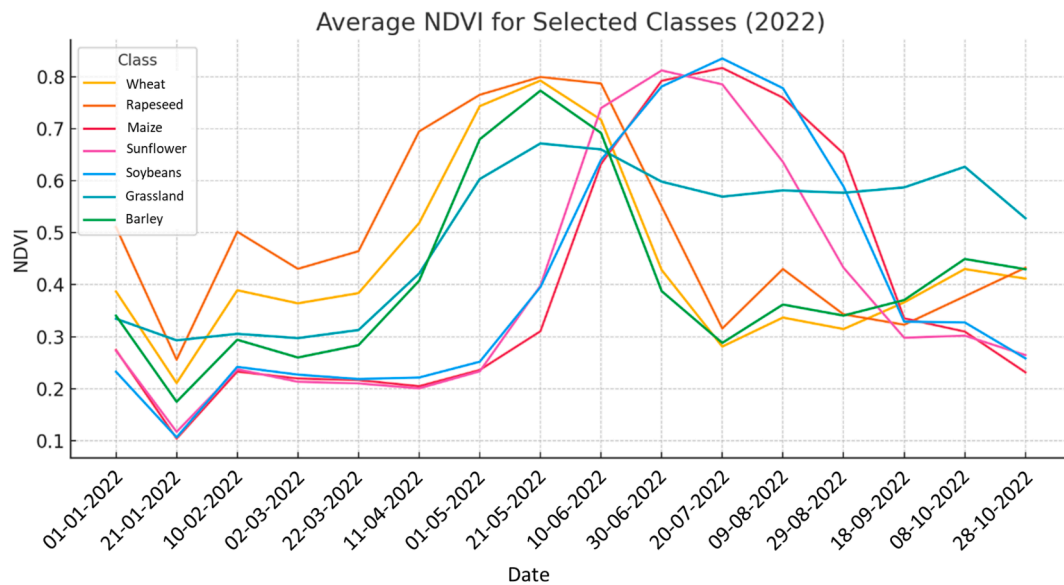


Fig. 3. Average values of NDVI for all fields in the in-situ dataset for the territory of Ukraine in 2022 for different crop types.

more data was directed toward training to improve classification accuracy.

The ground survey dataset, presented in Table 1, includes not only in-situ data collected through road surveys over the years but also non-crop classes such as artificial land, forest, grassland, bare land, water, and wetland. The non-agricultural classes in the dataset were augmented with data extracted through image interpretation of high-resolution satellite imagery. They are necessary for correct classification for the non-agricultural land cover/land use types.

In order to detect potential human error in the creation of the training data an experiment was run on the 2022 data set. Using multiple runs with an independent *teras_tcn* deep learning model, each with a different random selection of training and testing and validation in a proportion of 30–30–40, outliers in the ground data were detected by tracing multiple misclassifications to the training selection (Lemoine, 2023). This procedure identified 104 (e.g. 1.5 %) samples that were considered mislabelled. This confirms that the ground truth data is sufficiently reliable for the study, with the level of inconsistency falling within an acceptable margin of error.

To validate training and test data, NDVI time series for major crops like wheat, barley, and sunflower were analyzed from January to November 2024 using 20-day Sentinel-2 composites, created in Google Earth Engine. The cloud masking and composite generation method is described in Section 3.1, alongside the methodology for land cover/land use mapping.

Average NDVI values were calculated for each field, with graphs showing growth patterns. Fig. 3 shows patterns of all major crops. Wheat and rapeseed grow from mid-March, peaking in May, while sunflower and soybean start later in May. NDVI patterns confirm consistent vegetation trends across fields, ensuring data reliability.

The in-situ datasets collected along the roads were validated using deep learning techniques to detect outliers in the ground data (Lemoine, 2023). The analysis found that only about 1.5 % of the samples—in particular, 104 polygons for 2022—appeared to be outliers. This confirms that the ground truth data is sufficiently reliable for the study, with the level of inconsistency falling within an acceptable margin of error.

3. Methodology of the land cover/land use (LC/LU) mapping

In this section, we explore the classification process across different platforms, examining the data processing methods, classification algorithms and platforms.

3.1. LC/LU mapping with Random Forest

Google Earth Engine (GEE) is one of the most widely used platforms for large-scale land cover and crop classification. Our team has developed a land cover/land use (LC/LU) classification methodology for large territories using the GEE cloud platform, building on previous research (Kussul et al., 2023b; Shelestov et al., 2020; Shelestov et al., 2017a; Shelestov et al., 2017b).

The one of the major advantages of GEE is the direct access to satellite data, in particular Sentinel-1 backscatter coefficient ARD data, pre-processed with the SNAP toolbox after transferring GRD into the platform.

Our classification methodology requires Sentinel-1 composites for the entire territory of Ukraine. We select only Sentinel-1 data from the descending orbits, due to the occasional absence of complete ascending coverages. A mean composite is created for each 12-day period in the period 1 March to 1 September. Such composites typically average overlapping scenes from adjacent orbits. To reduce speckle noise, the resulting composites are filtered using the neighborhood mean filter with kernel 3.

For Sentinel-2, composites are also being created for the entire territory of Ukraine. For this, all Sentinel-2 granules of the Sentinel 2 Level 2A (atmospherically corrected surface reflectance) collection covering Ukraine with a per-scene cloud threshold of 40 % are selected. The period for creating the composite is chosen in such a way that as a result we get an image that is clear of clouds and without gaps. These dates are selected by an expert and the quality of the resulting composite is checked by an expert. Usually we can create 1 composite per month. For each granule, a cloud mask is applied, which is created based on the Scene Classification Layer (SCL, a band with 20 m resolution produced in the atmospheric correction processing step), masking the following classes on the satellite image: Cloud Shadows, Clouds Low, Medium, and High Probability, Cirrus, and Snow/Ice. The composite is created from all available satellite images within the selected period. In those pixels that were covered by multiple satellite images by different dates, the median of all available values is calculated. We have used four spectral bands with best 10 m spatial resolution (blue (B2), green (B3), red (B4) and near infrared (B8)) for each composite. We do not use other spectral bands because they have lower spatial resolution and their addition would increase the use of computational resources in the GEE. For this purpose, we conducted separate studies.

Creating optical composites for the entire country is a disadvantage

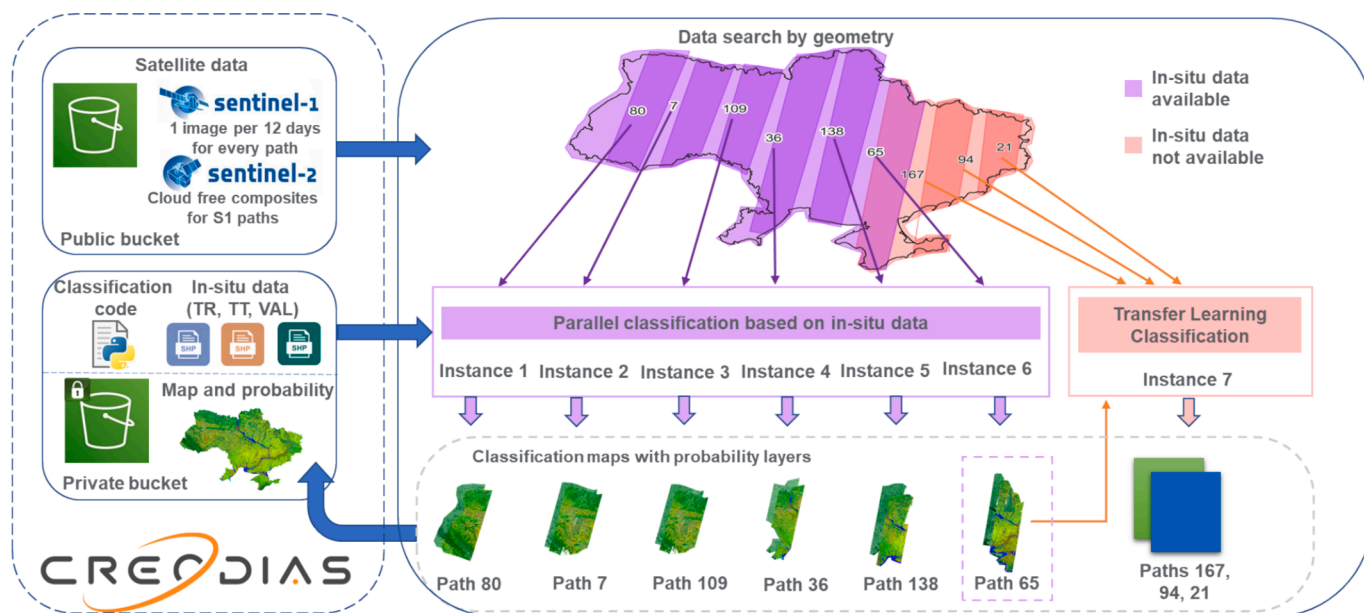


Fig. 4. Workflow for generating land cover classification maps on the CDSE cloud platform.

in this case, as we reduce the amount of informative data. However, it allows us to use full training dataset at once and train one model for the entire territory and build a map for areas with limited access to ground data collection (occupation zones or frontline areas, for example).

Since there is a resource constraint in the GEE, only centroids with a 3-meter buffer from entire polygons of the training data should be used to optimize resources. These centroids serve as labeled points for training the classification model effectively.

To train the classifier, all the resulting Sentinel-1 and Sentinel-2 composites, together with the training data, are combined into one stack and the Random Forest algorithm is used, which is one of the best algorithms in GEE. The resulting output of the program code is a classification map for all of Ukraine in.tif format, which is saved directly to the user’s Google Drive.

Another disadvantage of this approach of LC/LU classification is the underestimation of minority classes. In particular, this applies to sugar beets, buckwheat, potatoes and other less common crops in Ukraine. We try to fix this problem by using the Multi-Layer Perceptron and transfer learning.

3.2. LC/LU mapping with transfer learning

Since 2020 we utilize the CDSE cloud platform for generating our land cover maps, thanks to cloud access provided through the EU-supported e-shape and OCRE projects (Open Clouds for Research Environments). The OCRE project (Shelestov and Siemens, 2022; Blasco et al., 2020) funded by the European Union, facilitates cloud services to the European research community for efficient processing of large-scale Earth Observation data. This initiative enables access to Sentinel-2 Level 2A products, which include essential atmospheric corrections, enhancing the accuracy of land cover mapping.

Within the CDSE platform, we used satellite data from Sentinel-1 (descending) and Sentinel-2 from March till September of the current year. Both sensors are in a dual configuration consisting of the first-generation A and B satellites. Sentinel-1A and -B are active microwave sensors each with an interleaved 12-day revisit (resulting in an effective 6-day revisit until the premature loss of Sentinel-1B in December 2021). Each Sentinel-1 sensor requires nine (overlapping) paths to cover the entire territory of Ukraine (Fig. 4).

Contrary to Sentinel-2 data, Sentinel-1 data is only made available as Level-1 Single Look Complex (SLC) or Ground Range Detected (GRD)

format, neither of which is an analysis ready data (ARD) format. We use noise filtering as pre-processing of Sentinel-1 data in the open source Sentinel Application Platform (SNAP) (Filipponi, 2019) and produce ARD scenes as georeferenced backscattering coefficients in GeoTIFF format.

The georeferenced backscattering coefficient data is composed into single images for each of the nine paths for the entire growing season (March to September) resulting in a time series for each of the 2 polarization bands (VV and VH).

Sentinel-2A and -2B compose the dual sensor configuration with optical and infrared imaging capacities. Their combined use leads to an effective 5-day revisit. We generate Sentinel-2 composites by the territory of each Sentinel-1 path using the ARD Level 2A sensor products. For this, all Sentinel-2 granules covering the corresponding path with a cloud threshold of 40 % are selected. The number of individual scenes contributing to the composites vary depending on cloud cover during the growing season. Since the composite coverage area is smaller compared to the methodology in Section 3.1, we can shorten the time period for creating each composite by processing data in separate paths, thereby increasing the number of optical composites. However, in practice, we still typically generate one optical composite per month. For each granule, a cloud mask is applied and the composite is created as described in the Section 3.1.

Thus, for each Sentinel-1 path, we generate satellite images for specific dates for Sentinel-1, while for Sentinel-2, we create composites based on the available data.

The ground-based observation data is available for six (or five, depending on the year) paths, which is used for training (TR), validation (VAL), and testing (TT) classification models. For the remaining paths (eastern regions for all years and western regions in 2017), in-situ data don’t exists, necessitating the transfer and adaptation of models to generate classification maps for the whole country. Unlike the algorithm from Section 3.1, we use full polygons for training, not just the centroids with buffers. When **in-situ data is available** for the path, we employ a parallel processing approach to efficiently manage the large datasets required for land cover mapping in Ukraine. For this, pre-processing and classification are done simultaneously for each path on a separate computational instance. For Ukraine, these paths include numbers 80, 7, 109, 36, 138, and 65 (Fig. 4, highlighted in violet).

Training (TR) and testing (TT) data for the classification models are stored on a private bucket. Before training the model for each vegetation

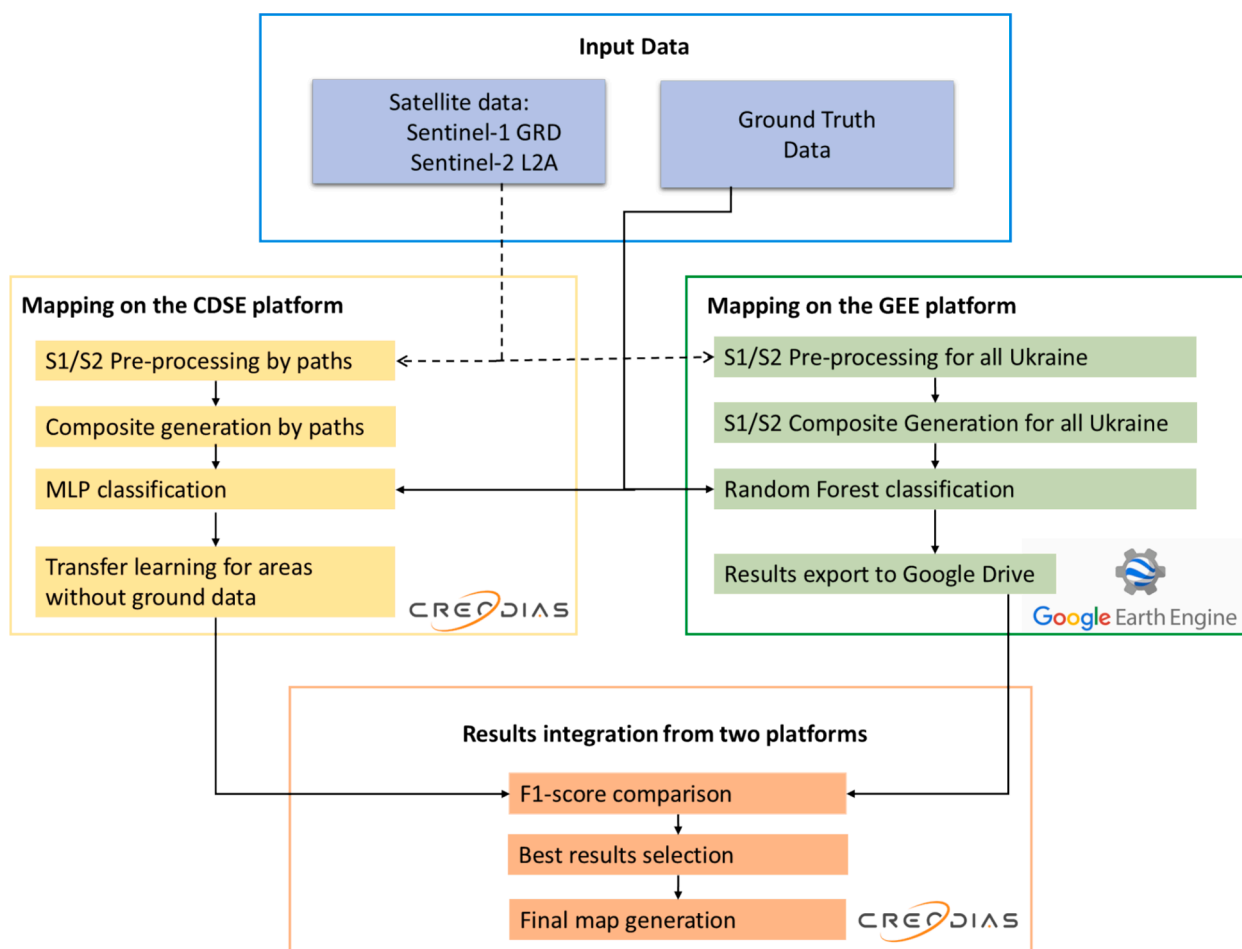


Fig. 5. Workflow and framework for generating land cover classification maps using the CDSE (yellow block) and GEE (green block) cloud platforms, with results integrated into the final product (orange block).

season, we split the datasets into training and testing sets for each region of Ukraine with available data. The testing data remains untouched until the final map’s accuracy is evaluated, while the training data is organized by Sentinel-1 path and stored in a bucket. Additionally, the classification and processing code is stored in the same bucket.

On the CDSE platform, we have flexibility in classifier selection, allowing us to utilize Multilayer Perceptron (MLP) neural networks for satellite data classification. To enhance accuracy, we apply an ensemble of classifiers. We prioritize MLP over deep learning models to maintain an optimal balance between classification efficiency and computational cost. Data is normalized using StandardScaler (Kramer, 2016), and class imbalance is handled with the SMOTEENN method (Hairani Hairani and Dadang Priyanto, 2023). MLP input dimensions are based on the number of satellite channels in each image and the number of composites in the time series. For Sentinel-1, each image provides two channels, while composites from Sentinel-2 include four channels at a 10-meter resolution. For example, if the time series during the vegetation period includes 18 Sentinel-1 images and 6 Sentinel-2 monthly composites, the input vector dimension would be $(18 \times 2) + (6 \times 4) = 60$. The hidden layers contain a variable number of neurons, with the optimal number determined with hyperparameter tuning via grid search. The output layer includes a number of neurons equal to the number of classes, and it uses a SoftMax activation function to convert the network’s outputs into probabilities. Meanwhile, the hidden layers use the ReLU (Rectified Linear Unit) activation function (Hara et al., 2015) to introduce non-linearity into the model. During the training of the neural network, we minimize the cross-entropy error function. To avoid overfitting, we apply L2 regularization (Cortes et al., 2012). The training process is set

to run for a maximum of 5000 iterations to ensure model convergence and optimal performance.

Each classifier in the ensemble outputs the posterior probability for each class, and the input pixel is assigned to the class with the highest probability. After generating classification maps for all nine paths, they are merged by selecting pixels with the highest probability in overlapping areas. This process ensures that each pixel is assigned the most accurate land cover class. The final unified map integrates results from all paths.

The output from each instance includes a raster classification map and probability map for each pixel, providing a probability score for each class. This information helps determine both the most likely class (for the classification map) and assess classification uncertainty. Both rasters are stored as Geotiff files on a private bucket, ensuring safe access for subsequent analysis and usage.

For paths **without training data**, we use a transfer learning approach. Since Sentinel-1 paths overlap, classification results from neighboring paths (Fig. 4, orange paths 167, 94, and 21) are utilized. Training data for a new path is generated from overlapping regions by selecting pixels with high classification probabilities (above 0.95) across land cover classes. We utilize evenly distributed pixels to ensure a balanced dataset.

One limitation of this approach is that the classification process for the satellite paths must be performed sequentially. Since the training data for each new path relies on the classification results of the previous path, work on new paths cannot begin until the classification of the previous one is completed. This sequential dependency can restrict the overall speed and productivity of the classification process. However,

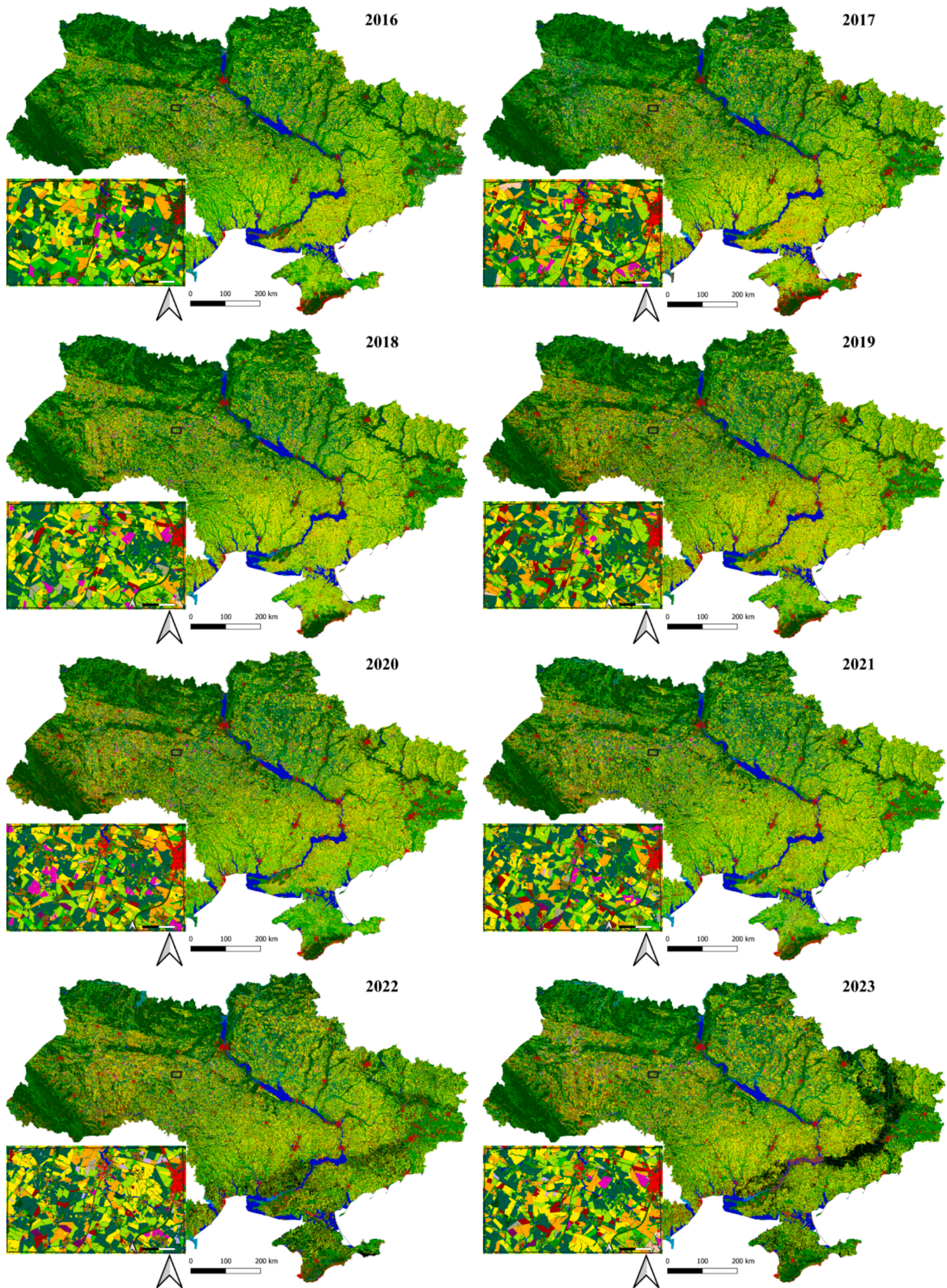


Fig. 6. Land Use classification KPI-Ukraine maps 2016–2024 generated with combined approach using GEE and CDSE platforms, with zoomed-in fragments highlighting detailed land use. Colors indicate different land use classes according to the legend.

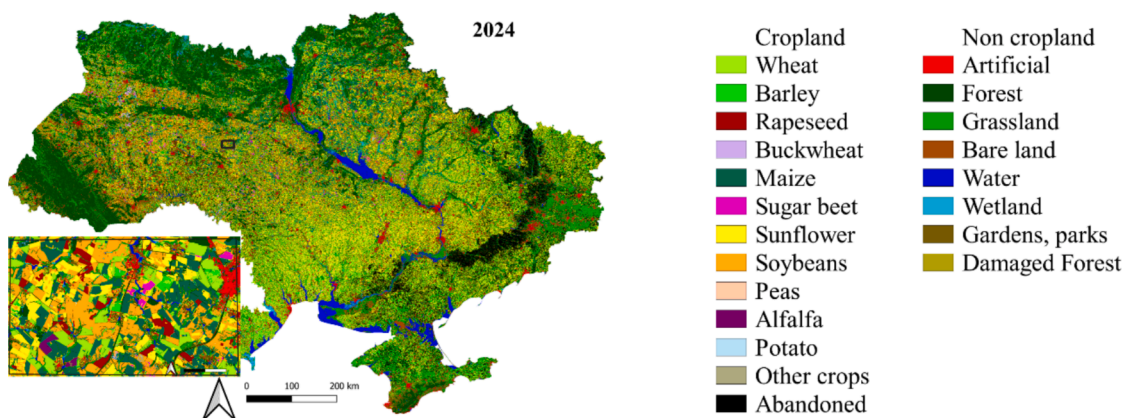


Fig. 6. (continued).

Table 2
F1-scores and overall accuracy of KPI-Ukraine maps 2016–2024.

	F1-score and overall accuracy of KPI-Ukraine classification maps									
	2016	2017	2018	2019	2020	2021	2022	2023	2024	
Cereals		96,9	98,8	97,8						
Wheat	90				91	97,9	96	94,5	92,9	
Barley	59,2				78,1	92,8	81,2	73,9	69,8	
Rapeseed	83,6	97	99,1	98,9	94,3	99,2	100	97,3	99,4	
Buckwheat	60,4			24	69,8	87,8	75	68,7	98,4	
Maize	93	92,1	96,9	96,9	91,8	99,1	94,5	92,4	96,4	
Sugar beet	93,6	98,6	95,5	86,6	89,4	99,4	92,9	94,5	95	
Sunflower	94,3	95,6	98	98,2	93,8	99,7	98,2	98,1	98,4	
Soybeans	82,5	81,6	92,3	86,9	82,4	96,2	82,2	88,7	94,4	
Peas	70,9	91,8	92,9	68,6	87,7	88,5	99,5	89,5	97,4	
Alfalfa				68,5	84,9	60,9	88,5	43,8	84,4	
Potatoes							86,7	30,1	49,8	
Grape				46,6	79,8	87,1	90,8	64,7	85,9	
Gardens, parks				59	56,3	83,3	89,5	85	71,7	
Other crops	34,5		66,8	34,4	19,6	72,9	16,3	71,1	20,6	
Artificial	75	70,3	78,3	70,6	74,1	93,4	95,8	85,2	86,2	
Forest	98,1	98,7	99,8	91	91,8	99	98,7	98,9	98,6	
Grassland	80,2	84,3	94,7	80,5	78	91,1	90	88,3	85,7	
Bare land	60	60,8	77,4	64	68	96	88,1	78,3	78	
Water	88,6	99,2	99	99,2	100	100	99,8	99,7	100	
Wetland	77,3	62,5	73,3	63,5	56,1	87,3	90,3	93,4	95,9	
Uncultivated land								92,2	93,2	
Overall accuracy	88,3	91	97,3	94,8	87,9	97,5	95	93,1	94,5	

this method ensures proper classification across paths and maintains high-quality results.

3.3. Framework for LC/LU classification

To leverage the strengths of both methods (Sections 3.1 and 3.2), we developed a general framework for LC/LU classification and mapping in Ukraine that integrates optical and radar satellite data. Our approach combines the capabilities of two leading cloud platforms: the Copernicus Data Space Ecosystem (CDSE, using CREODIAS cloud resources) and MLP classifier, (Fig. 5 – yellow block) and Google Earth Engine (GEE) and RF classifier (Fig. 5 – green block). A key advantage of these platforms is their access to the complete integrated satellite data repositories, particularly for the Copernicus Sentinel-1 and Sentinel-2 missions.

The classification process runs in parallel on both platforms, using the same Sentinel feature data, utilizing their unique features and algorithms.

The final classification map, called the KPI-Ukraine map, is generated by integrating results from two cloud platforms, GEE and CDSE (Fig. 5 – orange block). This approach takes advantage of the strengths of both platforms to improve overall classification accuracy (Section

4.2).

We merge results from GEE and CDSE based on F1-scores from both platforms. Initially, a base map is created from the intersection of classes ($Map_{GEE} \cap Map_{CDSE}$), with minor classes from CDSE ($MinorClasses_{CDSE}$) added. Any remaining gaps are filled using the most accurate class for each pixel:

$$Map_{KPI-Ukraine} = (Map_{GEE} \cap Map_{CDSE}) \cup MinorClasses_{CDSE} \cup MajorClass(\max(F1_score_{GEE}, F1_score_{CDSE})).$$

4. Validation of KPI-Ukraine maps

4.1. Accuracy assessment of KPI-Ukraine maps

The accuracy of our classification method was evaluated using F1-scores and overall accuracy for KPI-Ukraine maps generated for 2016–2024 (Fig. 6). The results, presented in Table 2, highlight the strengths and challenges of the method over time across various crop types and land use classes.

Major crops like wheat, barley, rapeseed, and maize showed strong accuracy, with wheat peaking at 97.9 % (2021) and barley improving to 92.8 % before declining due to limited data. Rapeseed and maize

Table 3
Comparison of F1-scores for RF, MLP, and combined map for 2024.

	RF Map	MLP Map	Combined Map (Map _{Result})
Artificial	86,7	79,8	86,2
Wheat	93,7	92,5	92,9
Rapeseed	99,4	99,2	99,4
Buckwheat	0,5	95,3	98,4
Maize	94,3	94,2	96,4
Sugar beet	72	91,7	95
Sunflower	95,2	98,7	98,4
Soybean	91,2	92,3	94,4
Other crops	10,2	12	20,6
Forest	93,2	95,1	98,6
Grassland	73,7	90,5	85,7
Bareland	79,9	78	80
Water	100	100	100
Wetland	94,7	78,1	95,9
Barley	69,1	69,7	69,8
Peas	84	97,2	97,4
Alfalfa	25,7	78,1	84,4
Garden / Low trees	71,5	84,5	71,7
Grape	83,6	90,2	85,9
Uncultivated	91,5	95,4	93,2
Potato	1,1	34,7	49,8
Overall accuracy	91,1	93,6	94,5

consistently performed well. Minor crops like buckwheat and soybeans improved significantly, though potatoes remain challenging due to small fields. Artificial land and wetlands also saw accuracy gains. Grassland classification accuracy improved over the years, stabilizing around 90 % by 2020. However, it declined to 88.3 % in 2023 and 85.7 % in 2024 due to the introduction of the “uncultivated land” class. This new class was added to monitor war-affected lands and shares similar spectral characteristics with grassland, complicating differentiation between the two. Overall accuracy peaked in 2021 at 97.5 %, with reliable results sustained by sufficient in-situ data and cloud-free satellite imagery. In 2024, our method maintained a solid performance of 94.5 %.

In general, the accuracy assessment shows that our classification method has consistently produced reliable results across various land use categories in Ukraine. The method performs particularly well in classifying major crops and key land use types, largely due to the availability of high-resolution 10-meter satellite data and a substantial amount of in-situ data. However, some minority crops and more complex land use classes still require further refinement to improve classification accuracy.

4.2. Comparison of classification accuracies across platforms and the benefits of data fusion

This section evaluates the accuracy of the 2024 land use map (F1-scores for land use classes) generated using RF in Google Earth Engine (GEE) and MLP in CDSE, emphasizing the advantages of combining data from both platforms.

Integrating maps from both platforms improves overall classification accuracy. Table 3 shows that Random Forest algorithm performs well for major classes but struggles with minor ones, often misclassifying due to spectral similarities. For example, potatoes were misclassified by RF, but MLP classifier successfully distinguished them, as shown in Fig. 7-a.

On the other hand, MLP provides higher accuracy for minor classes, particularly those like buckwheat, sugar beet, and peas, where the GEE

map underperformed or entirely failed to recognize the class. CDSE benefits from the use of neural networks, which offers a more refined classification of these minority classes.

RF is particularly effective at reducing noise in large homogeneous fields like maize (Fig. 7-b), minimizing “salt and pepper” artifacts. To create the final KPI-Ukraine map, F1-scores from both RF and MLP are compared, selecting the higher accuracy class for each pixel. This fusion approach leverages RF’s strength in major class accuracy and MLP’s ability to classify minor classes, resulting in a highly accurate, reliable final KPI-Ukraine map for all land use classes across Ukraine. This method highlights the benefits of integrating platforms and algorithms for large-scale classification tasks.

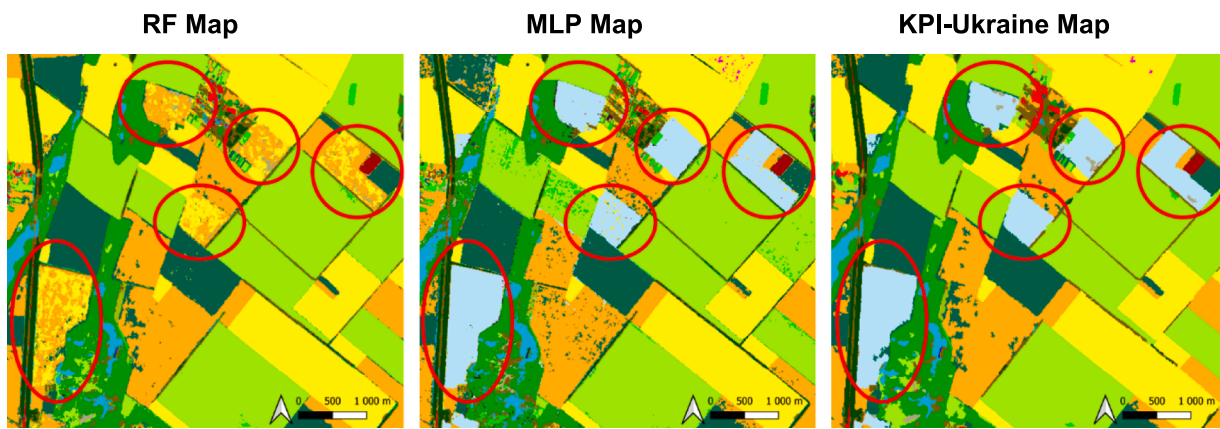
4.3. Accuracy assessment of the transfer learning approach

To evaluate land use maps generated through transfer learning, we conducted an experiment using in-situ data from the LPIS pilot project in 2024. Classification for path 109, based on in-situ data, was used to create maps for path 7 and 80 (Fig. 8), which are assumed to lack in-situ data. For each subsequent path, training data were extracted from the overlapping areas with the previous path, ensuring continuity and enabling classification even in the absence of direct in-situ data.

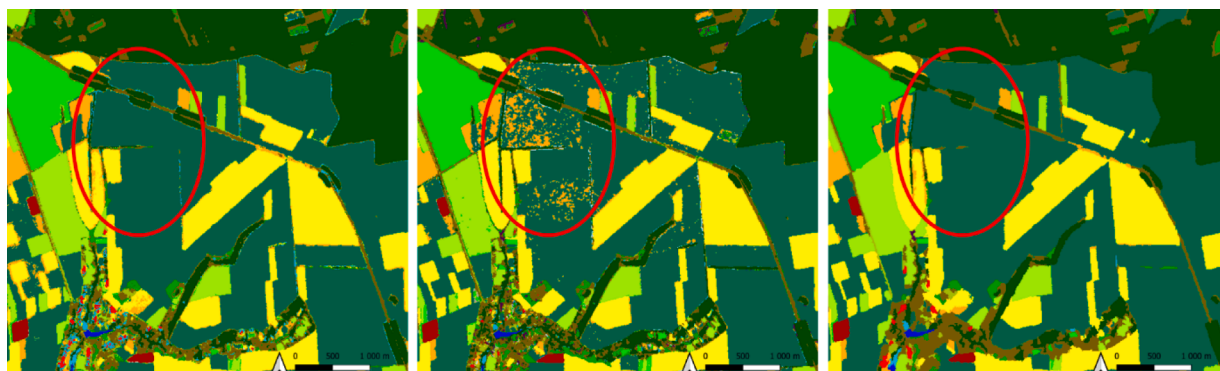
To generate the training dataset, we used vector field boundaries provided by Sinergise within EO4UA initiative (Kuzin et al., 2022), along with classification maps for each path that include class probabilities for every pixel. Fields were selected based on size (>100 m²) and classification probability (>0.95). Table 4 compares F1-scores of maps generated via transfer learning, RF, MLP, and the combined approach for paths 7 and 80, highlighting transfer learning’s effectiveness.

5. Analysis of trends in land use in Ukraine

The KPI-Ukraine map consistently outperforms both RF and MLP maps, with overall accuracy reaching 96 % for path 7 and 97.1 % for



a) MLP based map is strong in classifying minority classes like potatoes



b) RF map contains less "salt and pepper" noise on major classes like maize

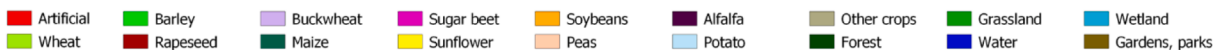


Fig. 7. Comparison of algorithms across cloud platforms with the combined KPI-Ukraine map. The left column shows a fragment of the RF map, the center column shows a fragment of the MLP map, and the right column illustrates the final KPI-Ukraine map. The top row (a) demonstrates the CDSE MLP’s strength to accurately classifying minority classes like potatoes. The bottom row (b) highlights the GEE RF classifier’s ability to reduce “salt and pepper” noise in major classes like maize.

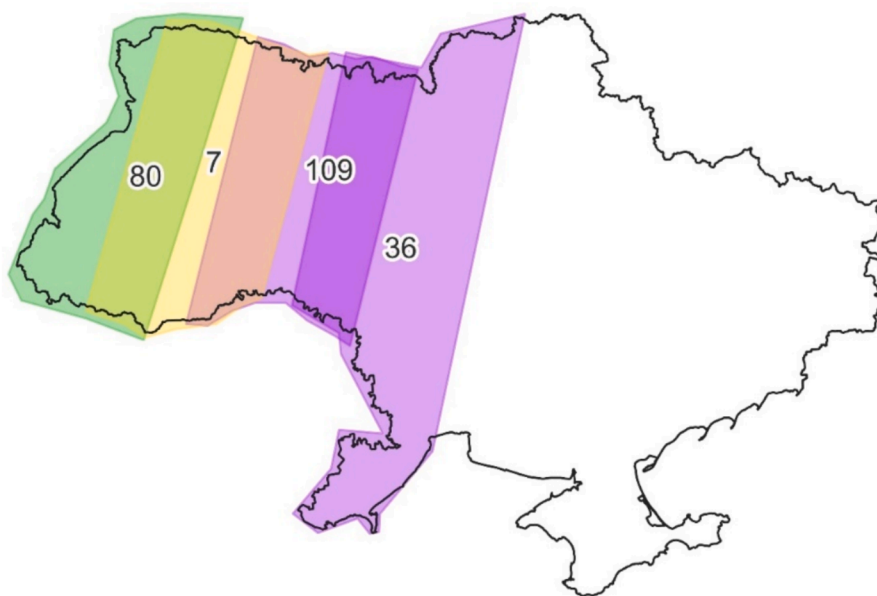


Fig. 8. Overlapping areas between paths used for generating training data. Paths 109 and 36 with in-situ data available are shown in purple, paths without in-situ data are shown in yellow (path 7) and green (path 80). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 4

Comparison of overall accuracies and F1-scores by class for maps generated using the overlap-based transfer learning approach (2024).

Class	F1-score							
	Path 7				Path 80			
	Overlap-based (109 & 7 paths)	RF Map (In-situ)	MLP Map (In-situ)	KPI-Ukraine	Overlap-based (7&80 paths)	RF Map (In-situ)	MLP Map (In-situ)	KPI-Ukraine
Artificial	96,4	93,2	95,9	98,9	89	85,9	90,2	97,4
Wheat	93,2	95,2	93,9	96,8	98,4	96,7	98,4	98,1
Rapeseed	99,2	98,3	99,2	99,7	99,7	95,4	99,7	99,6
Buckwheat	54,4	8,1	99,2	98,1	93,2	3,4	99	99,3
Maize	89,6	89,5	97,2	95,3	91,1	90,1	96,7	96,9
Sugar beet	11,4	59,4	84,7	95,1	29,4	74,8	71,4	91,6
Sunflower	91,6	88,2	97,3	97,5	74,3	54,1	92,8	96,5
Soybean	88,5	87,4	96,4	94,5	84,5	83,4	95,3	93,7
Other crops	25,3	33,9	26,4	50,2	6,4	30,8	7,3	72,9
Forest	97	97,7	96,4	99,5	99,4	99,6	99,8	99,5
Grassland	76,7	92,4	87,9	94,1	93,3	94,3	91,9	95,1
Bareland	90,7	90,7	82,6	97,8	89,6	91,9	87,5	95,7
Water	99,3	100	100	100	100	100	100	100
Wetland	25,7	78,5	73,5	57,2	62,6	76,9	69,4	75
Barley	63,1	83,3	71,9	89,4	13,2	69,3	71,8	78,3
Peas	8,3	82,8	6,9	99,7	0	81,1	75,4	100
Alfalfa	0	37,7	5,9	20,3	0	35,6	40,2	47,2
Garden / Low trees	73,6	74	50,5	93,8	69,9	74,8	52,9	84,2
Grape	77,8	0,6	78	94,9	90,5	95,6	98,9	95,9
Potato	0	25,2	69,9	70,1	11,1	22,9	57,2	68
Overall accuracy	88,8	89,2	94,5	96	91,2	87	96,1	97,1

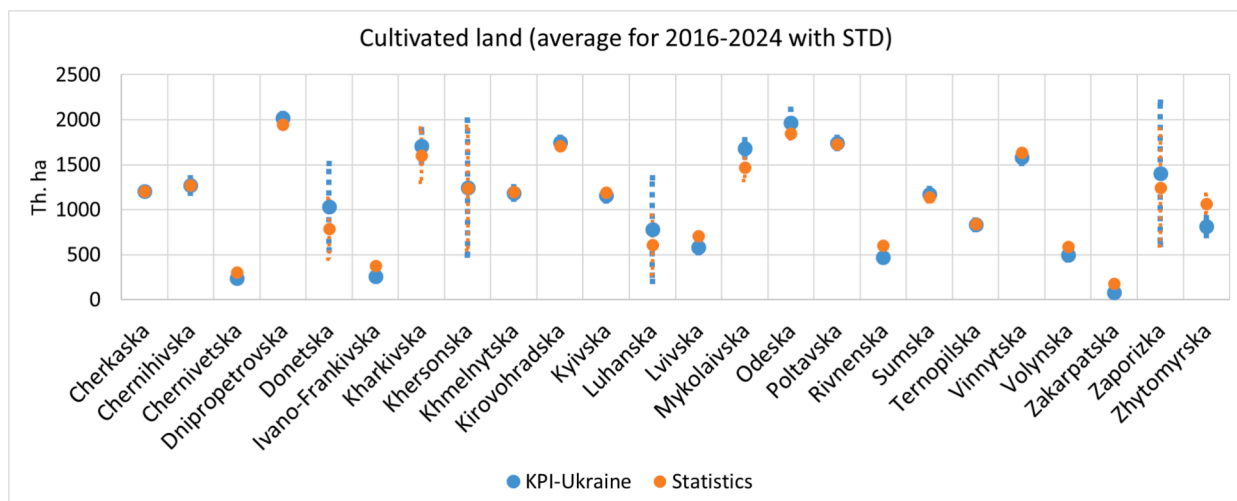


Fig. 9. Comparison of KPI-Ukraine crop area estimates with official statistical data at the oblast level.

path 80. RF excels at classifying major classes like wheat and water, while MLP is better with minor crops like buckwheat and potatoes. Transfer learning shows reasonable accuracy, particularly for non-agricultural classes, but struggles with minor crops. The fusion approach, combining strengths of RF and MLP, delivers the most accurate results, outperforming global products like ESA WorldCover and MODIS in classifying agricultural lands in Ukraine.

5.1. Comparison of KPI-Ukraine maps with official statistics and world cereal products

To assess the accuracy and reliability of the KPI-Ukraine maps, we conducted a comparative analysis against official agricultural statistics and other available land cover products. To maintain clarity and avoid overloading the paper with extensive data and figures, we provide a detailed comparison of cropland area estimates with official statistics and other products in the supplementary materials (Table 3s,

Table 5
Correlation of cropland and crop type area with official statistics (during 2022–2024 years we consider areas under government control).

	2016	2017	2018	2019	2020	2021	2022	2023	2024
Cropland	0,962	0,963	0,966	0,962	0,963	0,976	0,974	0,985	0,985
Sunflower	0,986	0,982	0,951	0,992	0,984	0,991	0,976	0,988	0,991
Maize	0,957	0,882	0,951	0,981	0,979	0,983	0,964	0,983	0,974
Cereal	0,958	0,964	0,940	0,979	0,968	0,982	0,929	0,980	0,982
Soybeans	0,936	0,850	0,674	0,928	0,953	0,927	0,928	0,953	0,984
Rapeseed	0,803	0,927	0,979	0,993	0,972	0,992	0,987	0,992	0,990

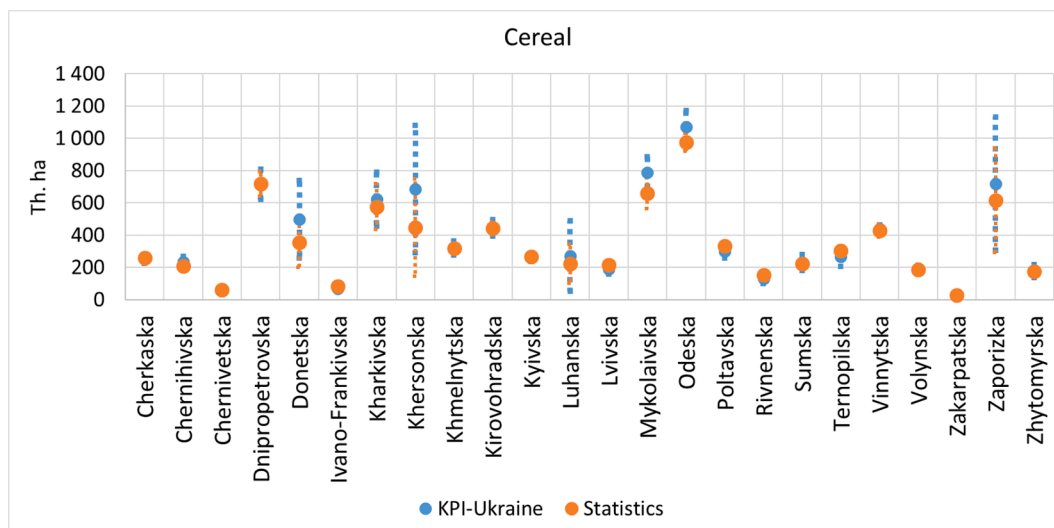


Fig. 10. Comparison of KPI-Ukraine cereal area estimates with official statistical data at the oblast level.

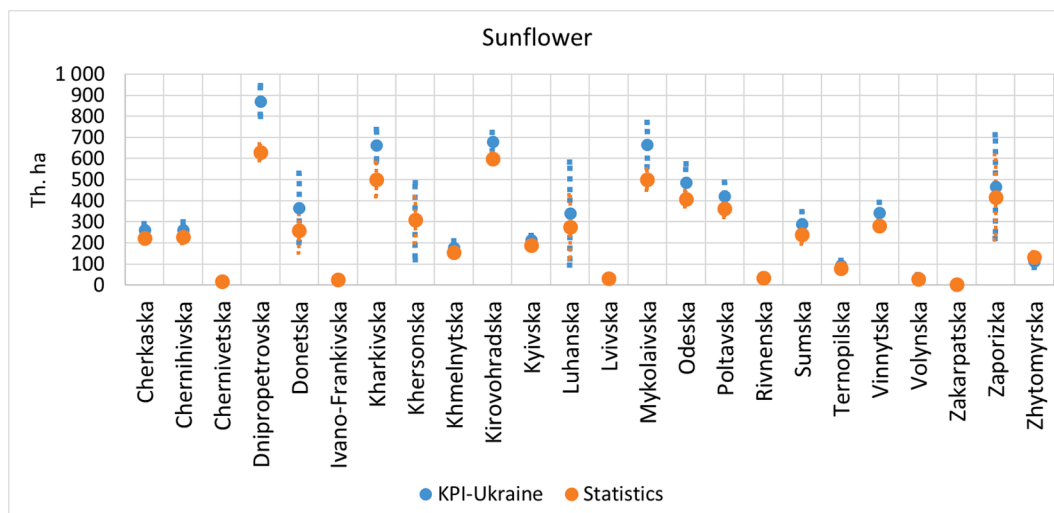


Fig. 11. Comparison of KPI-Ukraine sunflower area estimates with official statistical data at the oblast level.

Figs. 1s–6s). In the main text, we focus on the comparison of cropland area and major specific crops with official statistics and with World-Cereal crop maps, as they are the only available 10-meter resolution datasets for specific crops.

The KPI-Ukraine cropland area estimates were compared with official data from the State Statistics Service of Ukraine. For each oblast, we calculated the average values from 2016 to 2024 and estimated the standard deviation (STD) over this period. These indicators are visualized in Fig. 9, where bold dots represent the average values, and dotted lines indicate the STD. Significant deviations from official statistics are observed in war-affected regions such as Donetsk, Kherson, Luhans'ka,

and Zaporizhia. This discrepancy is explained by the partial occupation of Donetsk and Luhans'ka oblasts since 2014, with official statistics excluding data from occupied territories since then. Similarly, Kherson and Zaporizhia oblasts have been partially occupied since 2022, and the State Statistics Service cannot collect the data in these regions since the onset of the full-scale war.

The correlation between KPI-Ukraine estimates and official statistics across oblasts and years remains consistently high, ranging from 0.96 (2016–2020, 2022) to 0.97–0.98 (2023, 2024) for unoccupied territories (Table 5, Table 3s, Fig. 1s–6s). This strong agreement confirms the reliability of KPI-Ukraine for cropland area estimation. We also observe

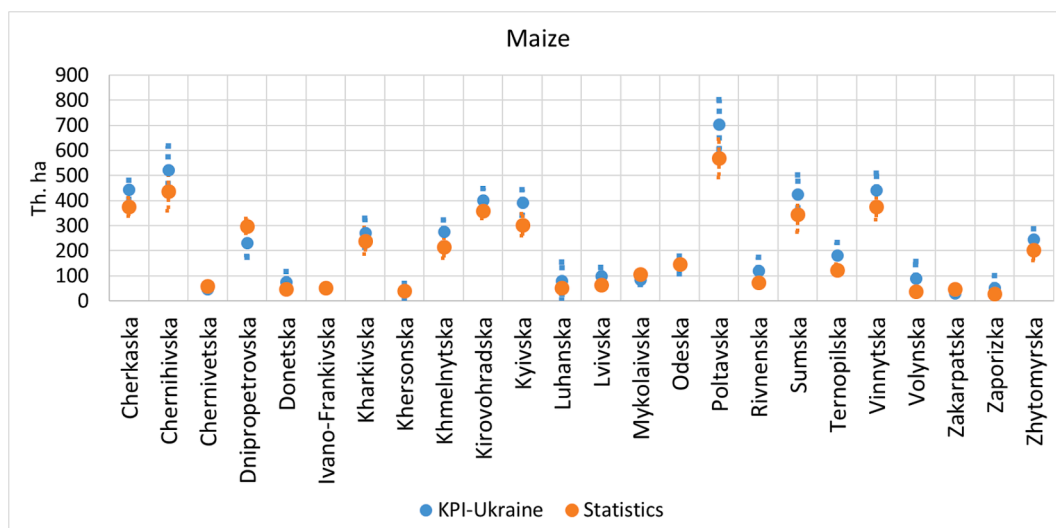


Fig. 12. Comparison of KPI-Ukraine maize area estimates with official statistical data at the oblast level.

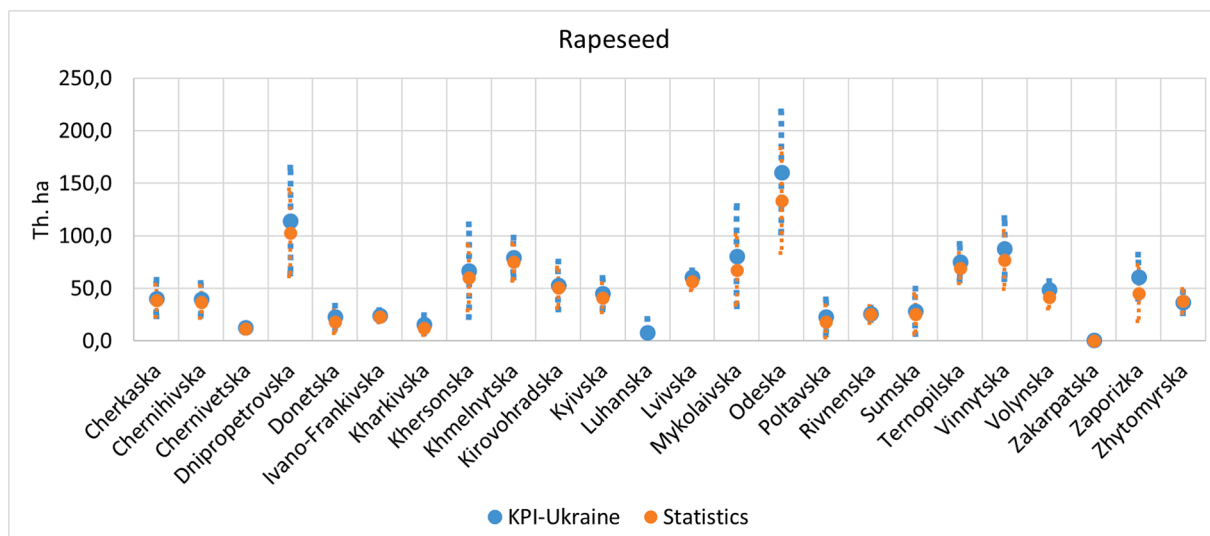


Fig. 13. Comparison of KPI-Ukraine rapeseed area estimates with official statistical data at the oblast level.

a high correlation for major crops – for sunflower area (more than 0.95), for maize (more than 0.95 except 2017), for cereal (more than 0.95 except 2022), for soybeans (more than 0.92 except 2017 and 2018) and for rapeseed (more than 0.97 except 2016 and 2017). The corresponding comparisons of average values for the main crops are shown in the Figs. 10–13. Furthermore, the results highlight the critical role of satellite-based agricultural monitoring, as satellite data remains the only objective source of agricultural statistics for occupied regions where ground-based data collection is no longer feasible.

In 2022 and 2023, NTUU “KPI” participated in the ESA World Cereal project (World Cereal project, 2024), validating WorldCereal maps for Ukraine using in-situ data. These maps, covering cereals and maize at 10-meter resolution, are the only publicly accessible global maps for these crops in Ukraine (Van Tricht et al., 2023). The Table 6 compares two classification products (WorldCereal and KPI-Ukraine) across four years (2018–2021), showing good user’s Accuracy (UA), Producer’s Accuracy (PA), and F1-scores for cereal and maize crops, along with overall accuracy. KPI-Ukraine consistently outperforms WorldCereal across most metrics in all years, 2020 was the weakest year for both products, particularly for cereal classification (which is most likely due to the severe drought and frosts of winter crops), 2021 shows the highest

performance for maize detection for both products.

Additionally, we compared cereal and maize areas at the oblast level between WorldCereal and KPI-Ukraine maps (Fig. 14) and estimated the correlation. The comparison showed a high level of correlation at the regional level, in particular above 0.92 (except 2018) for cereal crops and at 0.99 for maize for all years.

The comparison between KPI-Ukraine maps, official agricultural statistics, and WorldCereal products highlights the high reliability of our approach for monitoring cropland dynamics in Ukraine. This is particularly crucial during wartime, when official statistics do not cover the entire country, and global products offer limited crop diversity. KPI-Ukraine maps provide a more detailed and accurate representation of agricultural land use by integrating high-quality local in-situ data and state-of-the-art classification techniques.

5.2. Comparison of KPI-Ukraine maps with regional products

Unlike our KPI-Ukraine maps, no other regional-scale land cover products provide detailed multi-year crop classifications for Ukraine. As a result, a direct oblast-level comparison with alternative regional datasets is not possible. Instead, we evaluate the consistency of our

Table 6
Comparison of UA, PA and F1-score for WorldCereal products and KPI-Ukraine maps.

			Cereal	Maize	Overall Accuracy
2018	WorldCereal	UA	91	84	92,9
		PA	93	99	
		F1-score	92	91	
	KPI-Ukraine	UA	98,8	96,9	97,3
		PA	98,7	96,2	
		F1-score	98,8	96,9	
2019	WorldCereal	UA	93	86	93,6
		PA	96	97	
		F1-score	94	91	
	KPI-Ukraine	UA	96,3	95,7	94,8
		PA	99,3	98,1	
		F1-score	97,8	96,9	
2020	WorldCereal	UA	85	88	86,7
		PA	82	93	
		F1-score	83	91	
	KPI-Ukraine	UA	90,7	93,5	87,9
		PA	91,2	90,1	
		F1-score	91	91,8	
2021	WorldCereal	UA	99	98	95,3
		PA	90	98	
		F1-score	94	98	
	KPI-Ukraine	UA	97,3	98,6	97,5
		PA	98,5	99,5	
		F1-score	97,9	99,1	

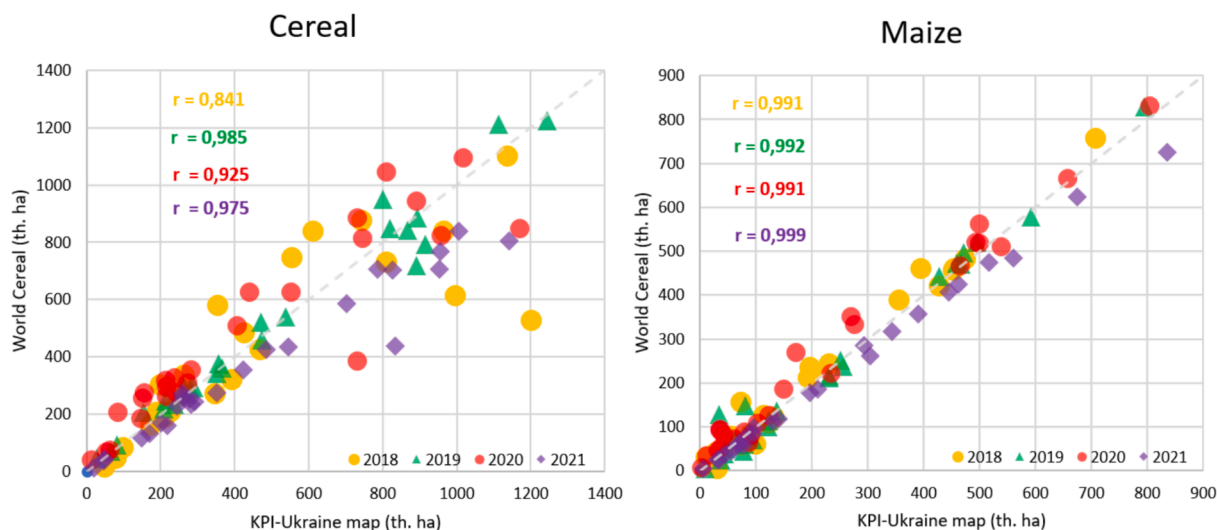


Fig. 14. Comparison of crop area estimates between WorldCereal and KPI-Ukraine maps at the oblast level with correlation (r) estimation.

findings by comparing them with reported results from existing studies on agricultural land use changes in Ukraine using remote sensing. Most of these studies rely on global datasets or focus on specific years and regions, whereas our approach offers a unique multi-year, high-resolution perspective, providing a more comprehensive understanding of cropland dynamics in Ukraine.

Compared with previous studies (Dai et al., 2024; He et al., 2023; Ma et al., 2022; Chen et al., 2024), our analysis reports higher estimates of abandoned land areas. This discrepancy arises because these studies rely on the ESA WorldCover 2020 global map, and do not incorporate ground-based observations or crop distribution data. As shown in Fig. 5s, ESA WorldCover 2020 overestimates cultivated areas, especially

in the south and east. Additionally, Ma et al. (2022) used satellite data only up to June 2022, basing their land cover maps on the global product GLC_FCS30-1985_2020, which further limits the reliability of their results.

Table 7 provides a detailed comparison of results from previous studies and our findings. Notably, our results closely align with those of Skakun et al. (2022) in estimating losses in sunflower cultivation areas. Unlike our study, other analyses did not provide specific estimates of lost areas for other individual crops.

KPI-Ukraine classification maps offer several key advantages over existing products for Ukraine, making them ideal for analyzing land use changes over the past nine years, including war-related disruptions.

Table 7
Comparison of the results of existing studies with this study (for 2022).

Source	LU change	Territory	KPI-Ukraine
Dai et al., 2024	7,14 % abandoned cropland	Ukraine	15 % abandoned cropland
He et al., 2023	7,17 % abandoned cropland	Khersonska, Zaporizka, Dnipropetrovska, Donetska, Luhanska Kharkivska	24 % abandoned cropland
Ma et al., 2022	22 % abandoned cropland	Khersonska, Luhanska	30,4 % abandoned cropland
	6 % abandoned cropland	Mykolaivska, Kharkivska, Chernihivska, Zaporizka, Donetska	20 % abandoned cropland
Chen et al., 2024	18,11 + -2,47 % abandoned cropland	AR of Crimea, Donetska, Khersonska, Luhanska, Zaporizka	32 % abandoned cropland
Skakun et al., 2022	-0,95 MLN ha of sunflower	Ukraine	-1 MLN ha of sunflower
Qadir et al., 2024	-5 % of sunflower area	Ukraine	-12,7 % of sunflower area

Table 8
Cropland Area in Ukraine (2016–2024) calculated from KPI-Ukraine map in comparison with official statistics for unoccupied territories.

Year	Cropland area from map, Thsd ha	Cropland area from map (unoccupied territories), Thsd ha	Cropland area from statistics, Thsd ha
2016	28361.3	26770.1	27026.0
2017	28669.0	27145.1	27585.2
2018	29463.4	27510.2	27699.3
2019	29442.3	27810.8	28000.8
2020	29748.1	28235.9	28147.5
2021	30756.6	29108.3	28580.9
2022	27722.3	22656.7	23272.4
2023	27021.9	23238.6	22745.8
2024	27256.3	23944.8	23235.5

*The statistical data in the table represent only croplands within the territory controlled by the Ukrainian government, while the cropland areas computed from the maps include the entire territory of Ukraine with Crimea (left column) and cropland areas on unoccupied territories (central column).

They provide a continuous nine-year time series (2016–2024), higher spatial resolution (10 m), and classification of 14 crop types, unlike global products which typically offer a generic cropland class. Essentially, KPI-Ukraine maps are produced in season with a final release in September of the current year. Latencies for other products are typically 2 years or more. Additionally, KPI-Ukraine maps capture war-related changes, validated with extensive field data, and leverage advanced cloud computing platforms, ensuring efficient processing and superior accuracy compared to global products like ESA WorldCover and MODIS (Tables 2s and 3s).

6. Analysis of trends in land use in Ukraine

In this section we use KPI-Ukraine maps for 2016–2024 to analyze trends in land use changes, particularly focusing on shifts in agricultural practices driven by the full-scale invasion.

6.1. Reduction in cropland area due to the war

One of the most significant war-related land use changes is the reduction in cropland. Following JECAM Guidelines (JECAM Guidelines, 2018), cropland is classified as land that has been cultivated at least once during the 12-month growing season. The cropland area was calculated by pixel counting on the KPI-Ukraine map using the UTM

projection (Zone 36 N), which minimizes distortion and ensures high accuracy for shape and area, making it suitable for precise spatial analysis in Ukraine.

Our KPI-Ukraine maps cover the entire country, including occupied territories, providing insights where official statistics are unavailable. Since Russia’s 2014 invasion, official cropland data has only been reported for government-controlled areas. Table 8 shows cropland areas from KPI-Ukraine maps 2016–2024 alongside official statistics, which only cover government-controlled regions since 2014. By comparing official statistics with KPI-Ukraine cropland maps, we find that over 1,000 ha of cropland were located in occupied territories after 2014. As shown in Table 8, area of cultivated land remained stable with slight yearly increases until 2021, reaching 30.7 million hectares (29.1 million in unoccupied territories). However, after the invasion, cropland area decreased by 10 % nationwide and over 22 % considering only unoccupied areas.

This reduction of cropland has left many fields uncultivated (abandoned). Identifying these abandoned fields is vital, as the government provides tax waivers for farmers unable to cultivate their land. Some studies define abandonment as any land cultivated in 2021 but left fallow during one or more war years. However, this approach oversimplifies the issue, as fields may remain fallow for soil health purposes rather than due to war-related factors.

To distinguish war-related abandonment from intentional fallowing, we generated a cropland mask based on multi-year observations. Following the recommendations of Balyuk et al. (2017) and Prymak et al. (2008), we identified cultivated fields as those farmed at least four times during the six pre-war years (2016–2021). This approach also aligns with the practices highlighted by Campbell et al. (2001), who suggest leaving fields fallow every 3–4 years to maintain soil organic carbon balance.

Fields within this cropland mask that remained uncultivated in 2022, 2023, or 2024 were considered as abandoned, in accordance with Estel et al. (2015) and Ma et al. (2022). This methodology provides a more precise identification of war-induced abandonment by distinguishing it from intentional fallowing.

Table 9 represents the abandoned land for 2023 and 2024, including cropland area difference between prewar period (2016–2021) and 2022–2024, using color intensity. The total abandoned area is 4.5 MLN ha for 2022 and more than 5 MLN ha for 2023 and 2024. The most affected regions are in southern and eastern Ukraine, including Zaporizka, Khersonska, and Donetska, which saw substantial cropland reductions. For example, Zaporizka experienced a 42.1 %, Khersonska a 46.4 %, and Donetska 66.9 % decline drop between 2016–2021 and 2024.

Fig. 15 shows the geographical distribution of uncultivated lands for several years prior to the full-scale war (2019–2021) and after the invasion (2022–2024) compared to cropland mask. The data is aggregated by hromadas, Ukraine’s smallest administrative units. The intensity of red indicates areas where cropland was left uncultivated (classified as grassland) year by year. Before the war, fallow land was evenly distributed due to typical agricultural practices, especially in the south and east. Since the war, however, there has been a sharp rise in uncultivated land, particularly near front-line areas.

KPI-Ukraine maps have been integrated into the State Agrarian Registry of Ukraine since its official launch as part of an EU and World Bank project in 2022. These maps assist in identifying uncultivated lands and support government decisions, such as granting tax waivers to farmers affected by the war.

Fig. 7s highlights the total land that was cultivated before the full-scale invasion but remained uncultivated at least once during the war in 2022, 2023, or 2024. In 2022, 4.5 million hectares were uncultivated, rising to 10.1 million hectares by 2024, reflecting war-related disruptions. Fig. 16 shows progressive abandonment: 0.9 million hectares have remained uncultivated from 2022 to 2024, likely due to contamination near front lines. These areas may require alternative post-war uses, like

Table 9
Changes in cropland area during the war (2022–2024) compared to the total cropland mask from the pre-war period (2016–2021).

	Cropland, th ha				Abandoned 2022		Abandoned 2023		Abandoned 2024		Abandoned 2022-2024	
	Cropland mask 2016-2021	2022	2023	2024	th ha	%	th ha	%	th ha	%	th ha	%
Donetska	1323,7	1109,7	803,2	662,4	386,6	29,2	792,6	59,9	885,9	66,9	191,4	14,5
Khersonska	1807,8	1115,1	987,7	995,2	688,5	38,1	739,6	40,9	838,0	46,4	190,7	10,5
Zaporizka	1960,1	1556,5	1372,9	1190,6	491,8	25,1	638,7	32,6	825,5	42,1	173,1	8,8
AR of Crimea	1118,9	650,6	685,0	705,6	638,8	57,1	617,5	55,2	609,3	54,5	162,0	14,5
Luhanska	1148,9	1066,9	829,3	698,2	206,5	18,0	486,5	42,3	598,8	52,1	57,4	5,0
Kharkivska	1807,2	1740,8	1413,7	1422,5	204,1	11,3	524,6	29,0	516,5	28,6	58,4	3,2
Dnipro-petrovska	2029	1984,2	1968,4	1960,1	157,2	7,7	154,0	7,6	173,5	8,6	12,0	0,6
Mykolaivska	1751,8	1475,7	1580	1699,5	322,5	18,4	220,0	12,6	130,1	7,4	24,7	1,4
Sumska	1139,8	1140,1	1270,5	1177,4	133,9	11,7	61,7	5,4	88,2	7,7	8,0	0,7
Chernihivska	1205,5	1318,4	1326,4	1323,4	149,3	12,4	128,3	10,6	86,5	7,2	19,0	1,6
Odeska	2046	1678,6	1834,3	2146,7	496,9	24,3	297,2	14,5	74,9	3,7	16,0	0,8
Zhytomyrska	731,2	918,1	882,8	896,5	65,9	9,0	71,6	9,8	42,6	5,8	6,4	0,9
Rivnenska	407,7	533	514,3	527	37,2	9,1	47,2	11,6	35,0	8,6	5,1	1,3
Poltavska	1695,1	1785,1	1803,8	1809,2	62,7	3,7	67,8	4,0	33,4	2,0	4,0	0,2
Volynska	443	543,9	517,1	575	43,4	9,8	61,0	13,8	25,9	5,8	5,1	1,2
Kyivska	1112,9	1202,5	1211	1233,6	62,2	5,6	52,4	4,7	24,9	2,2	5,3	0,5
Kirovohradska	1725,9	1748,9	1771,7	1803,9	61,6	3,6	63,4	3,7	20,0	1,2	2,0	0,1
Lvivska	519,5	627,6	623,7	681,4	48,9	9,4	50,4	9,7	15,4	3,0	3,2	0,6
Khmelnytska	1134,2	1222,9	1242,7	1265,8	49,7	4,4	47,7	4,2	13,5	1,2	2,4	0,2
Vinnyska	1520,4	1632,1	1635,7	1669,4	55,1	3,6	56,7	3,7	10,0	0,7	1,6	0,1
Cherkaska	1170,2	1233,2	1228,2	1250,7	24,8	2,1	41,7	3,6	8,7	0,7	1,2	0,1
Ternopil'ska	817,6	863,6	874,4	884,9	39,1	4,8	30,9	3,8	8,3	1,0	1,6	0,2
Zakarpatska	74,4	83,7	88,9	82,1	26,5	35,6	12,4	16,7	6,0	8,1	0,7	0,9
Ivano-Frankiv'ska	231,3	277,6	293,7	312,9	32,0	13,8	17,0	7,3	4,2	1,8	0,7	0,3
Chernivetska	223,3	213,6	262,4	282,5	51,8	23,2	17,2	7,7	2,5	1,1	0,5	0,2
Ukraine total	29145	27722	27022	27257	4537,0	15,6	5298,0	18,2	5078,0	17,4	952,2	3,3

reforestation, as they may be unsafe for agriculture.

6.2. Area trends for the major crops in Ukraine before and during the war

Fig. 17 analyzes crop area changes at the oblast level, comparing trends from 2016 to 2021 with those during the war (2022–2023 and 2022–2024). Green indicates an increase in crop areas before and after the war, red shows consistent decreases, yellow highlights reversals (decrease before, increase after), and orange shows the opposite (increase before, decrease after). The right column features bar charts for specific crops, including cereals and maize, tracking trends by oblast. Shadowed areas in the figure represent occupied territories.

Fig. 17 shows significant trends in crop areas before and during the war. Central Ukraine saw an initial increase in cultivated land, but by 2024, regions like Sumy experienced a decline due to military activity. Cereals and maize cultivation decreased overall, with a small rise in maize in Odesa and Kirovohrad in 2024. Sunflower cultivation initially grew but declined by 2024, except in key regions like Kirovohrad. In contrast, rapeseed and soybean cultivation surged during the war, especially in non-frontline regions. This shift may affect soil health and Ukraine’s agricultural market role.

7. Discussion

The results of this study provide a comprehensive multi-year analysis of agricultural land use changes in Ukraine before and during the ongoing war, leveraging high-resolution remote sensing data and machine learning approaches. This section discusses the key findings, their implications, methodological limitations, and potential directions for future research.

The analysis of KPI-Ukraine maps from 2016 to 2024 reveals substantial disruptions to agricultural land use due to the war. The most significant changes are observed in the reduction of cultivated croplands and the expansion of uncultivated land, particularly in conflict-affected regions. This trend is evident in the sharp decline in cultivated areas for major crops such as wheat, maize, and sunflower, which are among Ukraine’s primary agricultural exports. The decline in cropland is attributed to multiple war-related factors, including direct land destruction, logistical disruptions, labor shortages, and overall economic instability affecting the agricultural sector.

These findings align with previous studies (He et al., 2023; Dai et al., 2024; Ma et al., 2022), which reported similar trends in agricultural land abandonment following the invasion. However, the present study extends beyond single-year analyses by providing a systematic, multi-year perspective on these changes, confirming that the war’s impact is not limited to 2022 but continues to affect agricultural production in

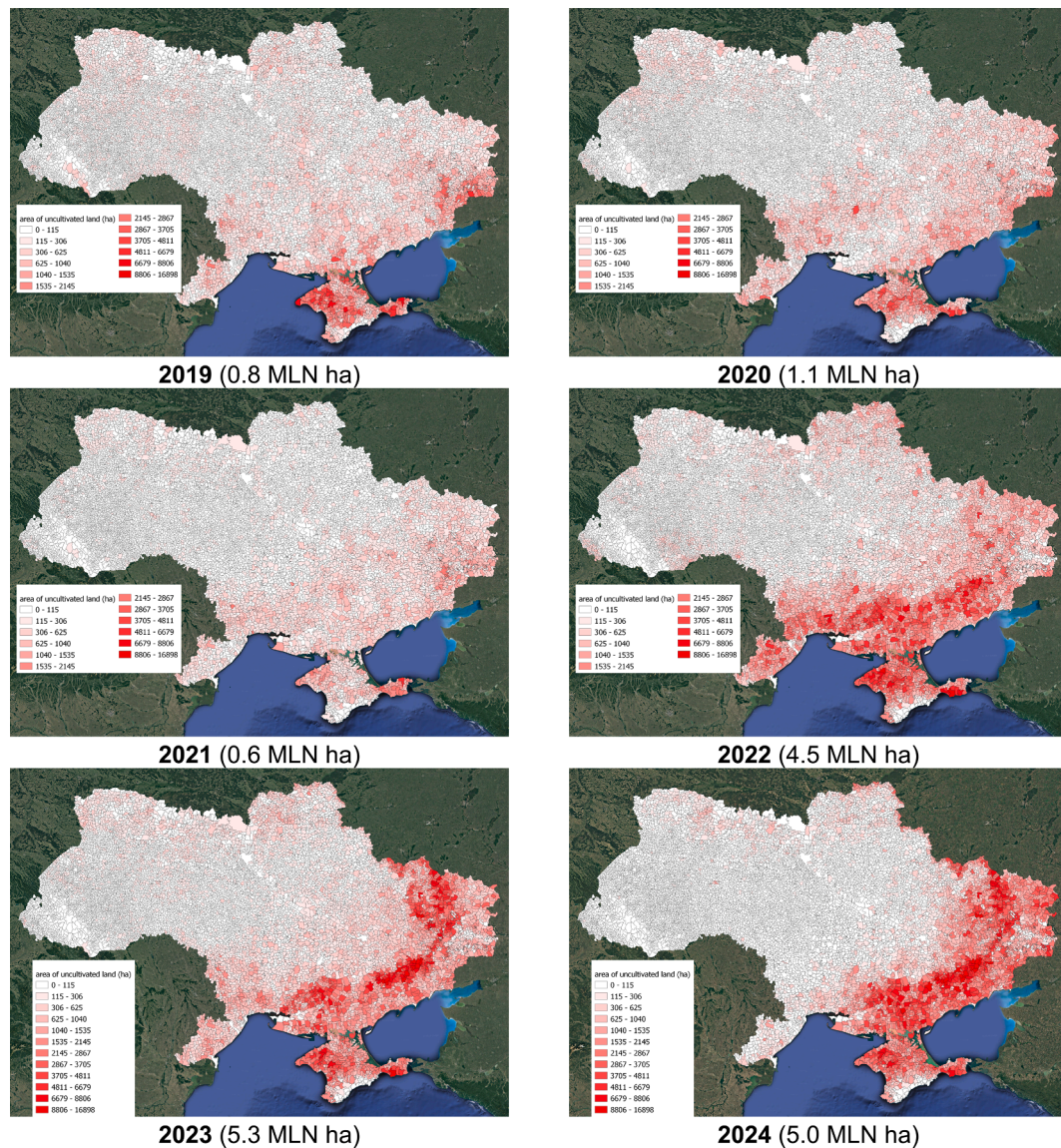


Fig. 15. Areas of uncultivated lands in Ukraine in 2019 – 2024 aggregated by hromadas (the smallest administrative units in Ukraine), identified based on the cropland mask.

subsequent years.

We validated the KPI-Ukraine maps against official statistics and the only available global crop specific product WorldCereal. The results demonstrate a high correlation between the KPI-Ukraine maps and official agricultural statistics, with R^2 values consistently above 0.95 at the oblast level. This strong agreement suggests that satellite-based classification provides an effective alternative for monitoring agricultural land use, particularly when ground-based observations are limited due to conflict.

The comparison with WorldCereal products highlights the strengths of the KPI-Ukraine methodology. While WorldCereal maps offer a valuable global perspective, their classification accuracy for Ukrainian crops is a bit lower than that of KPI-Ukraine. This discrepancy arises because WorldCereal maps are based on a global model that lacks region-specific training data, whereas KPI-Ukraine maps benefit from in-situ data collected over multiple years. The integration of localized training data thus significantly enhances classification accuracy for regional-scale applications, especially for multi-crop classification.

The study demonstrates the effectiveness of combining machine learning models across multiple cloud computing platforms—GEE and CDSE. The integration of RF classifiers from GEE and MLP models from

CDSE allows for improved classification accuracy by leveraging the strengths of both approaches.

The RF model excels in reducing classification noise for dominant land cover types, such as wheat, maize, and sunflower, while the MLP model is particularly effective in distinguishing minor crop types that are often misclassified in RF-based approaches. By combining these methods, the KPI-Ukraine map achieves a balanced classification, with overall accuracy constantly exceeding 90 %. This hybrid approach overcomes limitations of single-platform methodologies and demonstrates the benefits of data fusion in large-scale agricultural monitoring.

A major innovation of this study is the use of transfer learning to classify land use in regions where in-situ data is unavailable. By leveraging classification results from overlapping satellite paths, this approach enables the generation of accurate land cover maps even in war-affected areas where traditional ground-based data collection is infeasible.

The validation of the transfer learning approach using the LPIS pilot dataset shows that classification accuracy remains high, with an overall accuracy of 96–97 %. However, minor crop classes still exhibit higher classification uncertainty compared to major crops, primarily due to limited training samples. Future improvements could focus on refining

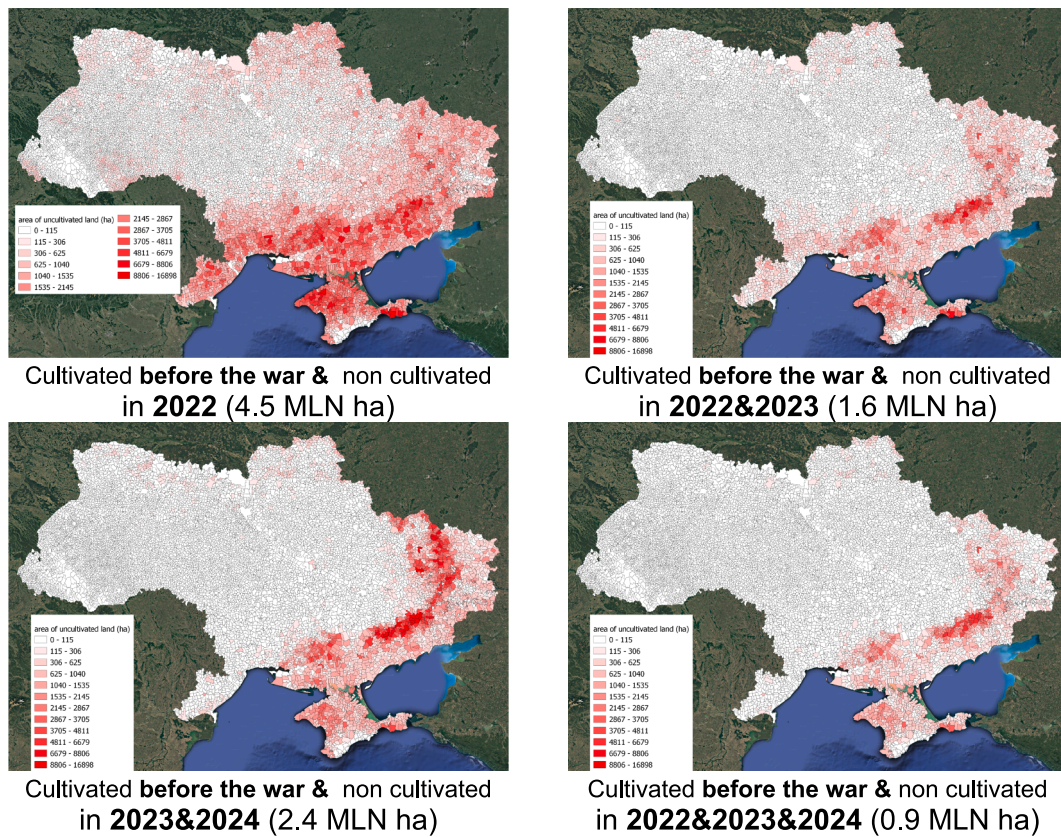


Fig. 16. Analysis of uncultivated lands (land uncultivated throughout all vegetative seasons during the war).

the transfer learning model by incorporating additional satellite-derived features or using semi-supervised learning techniques to further enhance classification performance in data-sparse environments.

Despite the high accuracy of KPI-Ukraine maps, several challenges remain that affect the classification process. One of the main limitations is the availability and quality of in-situ training data, which plays a crucial role in ensuring accurate classification. In conflict-affected regions, access to reliable ground truth data is restricted, leading to uncertainties, particularly for minor crops and heterogeneous land cover types. The lack of comprehensive validation data complicates efforts to refine classification models, making it difficult to achieve consistent accuracy across all agricultural classes.

Another challenge arises from the spectral similarities between certain land cover types, particularly uncultivated land and grasslands. These categories often exhibit overlapping spectral characteristics, making it difficult to distinguish between them using conventional classification techniques. While the hybrid approach integrating Random Forest and Multi-Layer Perceptron models helps reduce some of these ambiguities, further improvements are necessary. The integration of additional spectral indices, time-series analysis, or deep learning-based feature extraction could enhance differentiation and improve classification accuracy for such closely related classes.

In addition to data-related issues, computational constraints pose another significant challenge. Processing large-scale satellite datasets over multiple years requires substantial computational power, particularly when applying machine learning models at a national scale. Cloud-based platforms such as GEE and the CDSE provide essential tools for handling large volumes of remote sensing data, yet real-time monitoring remains a computationally intensive task. Optimizing AI-driven workflows, improving algorithm efficiency, and leveraging advancements in cloud computing could help streamline data processing, making large-scale classification efforts more efficient and scalable.

The insights from this study are critical for policymakers,

agricultural stakeholders, and international organizations involved in Ukraine's recovery. The identification of agricultural hotspots affected by the war provides valuable information for targeted land restoration and rehabilitation efforts. Additionally, the ability to monitor cropland dynamics at a national scale supports decision-making related to food security, economic stability, and post-war land management strategies.

Furthermore, the integration of Earth Observation (EO) data with machine learning presents a scalable solution for agricultural monitoring beyond Ukraine. Similar methodologies could be applied in other conflict-affected or data-limited regions, demonstrating the broader applicability of satellite-based land use classification for crisis management and recovery planning.

8. Conclusions

This study presents a comprehensive multi-year analysis of agricultural land use changes in Ukraine before and during the ongoing war, utilizing high-resolution remote sensing data and machine learning approaches. The findings reveal significant disruptions to Ukraine's agricultural sector, particularly the reduction of cultivated land and the expansion of uncultivated areas in conflict-affected regions. By leveraging satellite imagery from Sentinel-1 and Sentinel-2, combined with machine learning techniques on cloud platforms, the KPI-Ukraine classification maps provide a reliable and scalable approach for monitoring land use dynamics in crisis conditions.

The integration of classification models across GEE and the CDSE demonstrates the advantages of combining RF and MLP approaches. This hybrid methodology significantly improves classification accuracy, particularly for distinguishing minor crop types and reducing misclassification noise. Additionally, the implementation of a transfer learning approach enables accurate land use classification even in regions where in-situ data collection is unavailable, making it a valuable tool for monitoring agricultural areas in conflict-affected zones.

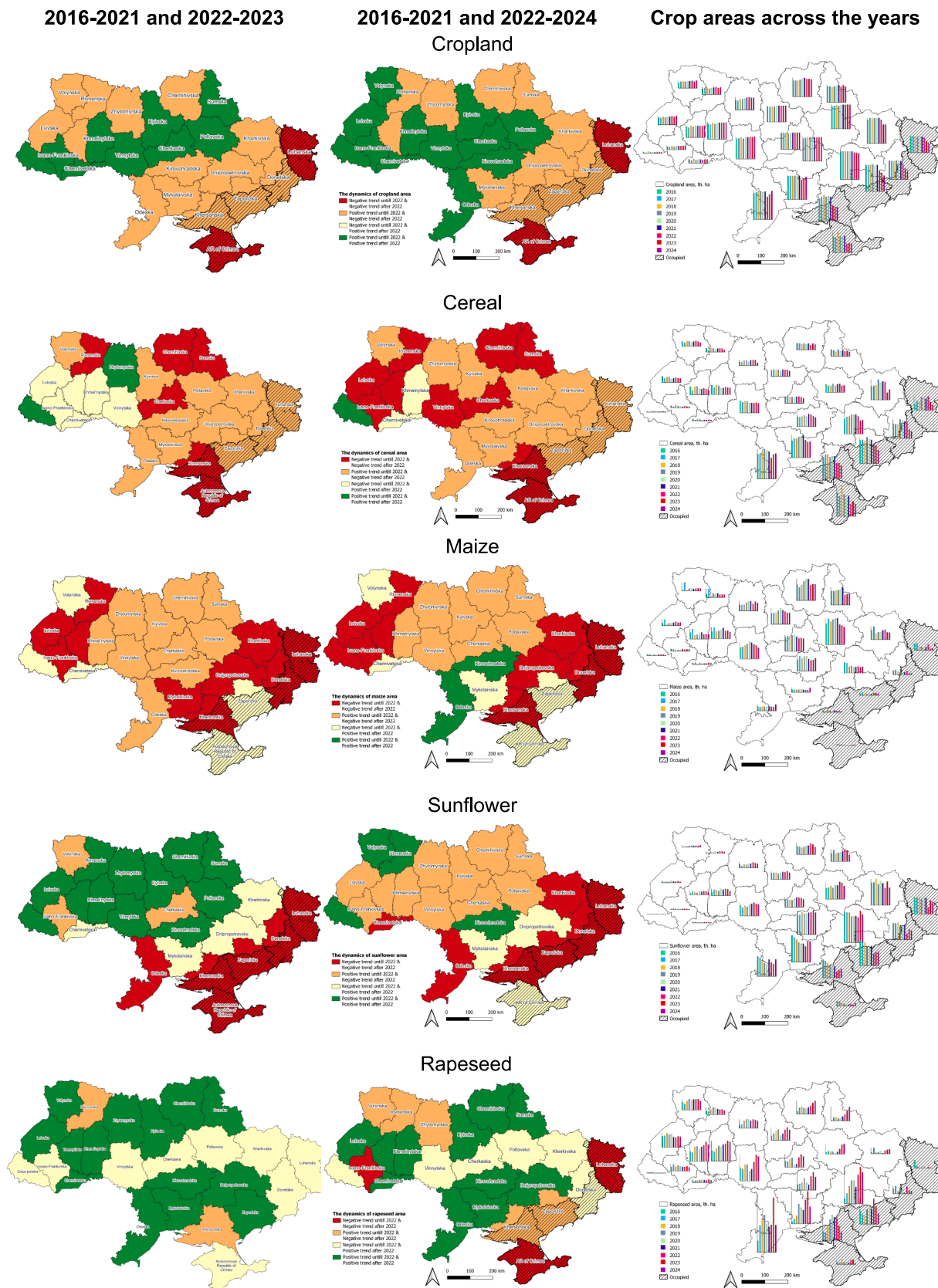


Fig. 17. Trends in crop area changes at the oblast level before and after the war. The left column – crop area trends for 2016–2021 and 2022–2023; the central column– crop area trends for 2016–2021 and 2022–2024. Green indicates a consistent increase in crop area, red a consistent decrease, yellow shows a decline before the war and an increase during the war, and orange indicates the opposite. The right column presents bar charts of crop areas at the oblast level across the years. Shaded area shows occupied territories. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

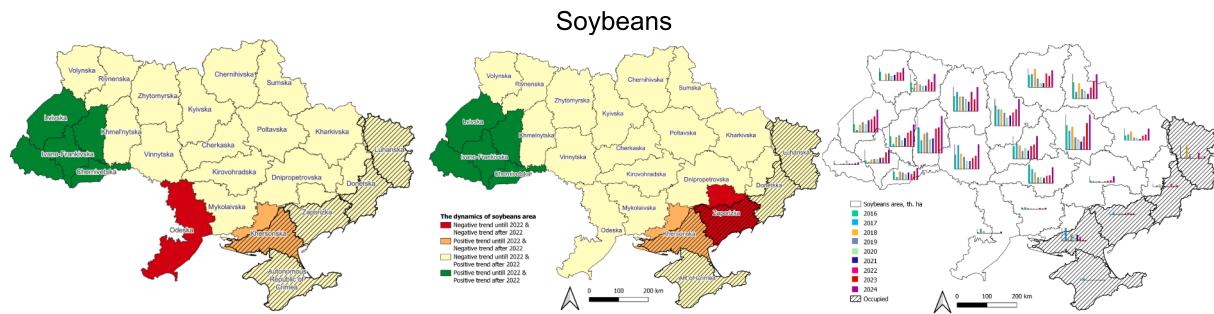


Fig. 17. (continued).

Our study highlights the critical importance of high-resolution, time-series land use classification maps for understanding the impact of conflict on agriculture and guiding post-war reconstruction efforts. The war in Ukraine has severely disrupted the agricultural sector, with significant implications for global food security. By utilizing innovative classification techniques that combine cloud computing, advanced algorithms, and extensive field validation, we have enhanced the accuracy and efficiency of large-scale agricultural monitoring in conflict-affected regions. This approach allowed us to address key scientific questions and bridge the identified research gap. Our spatially explicit assessment of war-induced land use changes serves as a valuable resource for policymakers, researchers, and international organizations working towards a sustainable and resilient agricultural future for Ukraine. As global challenges from conflicts and climate change continue, the methods and findings from this study offer a robust model for monitoring and managing land use dynamics in other crisis-affected regions.

CRedit authorship contribution statement

Nataliia Kussul: Writing – original draft, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Andrii Shelestov:** Writing – review & editing, Supervision, Project administration, Methodology, Investigation, Conceptualization. **Bohdan Yailymov:** Visualization, Validation, Software, Methodology, Data curation. **Hanna Yailymova:** Writing – review & editing, Visualization, Resources, Formal analysis. **Guido Lemoine:** Writing – review & editing, Methodology, Formal analysis, Conceptualization. **Klaus Deininger:** Writing – review & editing, Investigation, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was supported by the European Commission through the joint World Bank/EU project ‘Supporting Transparent Land Governance in Ukraine’ [grant numbers ENI/2017/387-093 and ENI/2020/418-654], expert contracts EC Joint Research Center (JRC) [CT-EX2022D670387-101, CT-EX2022D670387-102], National Research Foundation of Ukraine project ‘Geospatial monitoring system for the war impact on the agriculture of Ukraine based on satellite data’ [grant number 2023.04/0039] (impact of war on agricultural land cultivation), ‘DT4LC: Developing Scalable Digital Twin Models for Land Cover Change Detection Using Machine Learning’ [grant number 2023.01/0040] (impact of war on land use change), Ministry of Education and Science of Ukraine ‘Information technologies of geospatial analysis of the development of rural areas and communities’ [grant number PH/27-2023].

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jag.2025.104551>.

Data availability

Data will be made available on request.

References

- Avenza Maps. <https://www.avenza.com/> (accessed 30 September 2024).
- Balyuk, S., Medvedev, V., Kucher, A., Solovye, V., Levin, A., Kolmaz, Y., 2017. Soil organic carbon management in the context of food security and climate change. *Bull. Agric. Sci.* 95 (9), 11–18. <https://doi.org/10.31073/agrovisnyk201709-02> (in Ukrainian).
- Ben Hassen, T., El Bilali, H., 2022. Impacts of the Russia-Ukraine war on global food security: towards more sustainable and resilient food systems? *Foods* 11 (15), 2301. <https://doi.org/10.3390/foods11152301>.
- Blasco, J.M.D., Romeo, A., Heyns, D., Fernandes, J., Carrillo, R., Antoniou, N., Begin, M.E., 2020. The H2020 ocre project opens the gates of the commercial cloud and EO services usage to the research community. *Emerg. Sci. J.* 4 (2), 89–103. <https://doi.org/10.28991/esj-2020-01213>.
- Campbell, C.A., Zentner, R.P., Selles, F., Liang, B.C., Blomert, B., 2001. Evaluation of a simple model to describe carbon accumulation in a Brown Chernozem under varying fallow frequency. *Can. J. Soil Sci.* 81 (4), 383–394. <https://cdnsiencepub.com/doi/pdf/10.4141/S00-082>. <https://doi.org/10.4141/s00-082>.
- Chai, L., Liu, A., Li, X., Guo, Z., He, W., Huang, J., Liu, J., 2024. Telecoupled impacts of the Russia-Ukraine war on global cropland expansion and biodiversity. *Nat. Sustain.* 7 (4), 432–441. <https://doi.org/10.1038/s41893-024-01292-z>.
- Chen, B., Tu, Y., An, J., Wu, S., Lin, C., Gong, P., 2024. Quantification of losses in agriculture production in eastern Ukraine due to the Russia-Ukraine war. *Commun. Earth Environ.* 5 (1), 336. <https://doi.org/10.1038/s43247-024-01488-3>.
- Copernicus access to data, 2021. Copernicus component of the Space Programme in line with Regulation (EU) 2021/696 of the European Parliament and of the Council of 28 April 2021 establishing the Union Space Programme. <https://www.copernicus.eu/en/access-data> (accessed 22 October 2024).
- Cortes, C., Mohri, M., Rostamizadeh, A., 2012. L2 regularization for learning kernels. *arXiv preprint arXiv:1205.2653*. doi: 10.48550/arXiv.1205.2653.
- Countryman, A.M., Litvinov, V., Kolodiaznyi, I., Bogonos, M., Nivievskiy, O., 2024. Global economic effects of war-induced agricultural export declines from Ukraine. *Appl. Econ. Perspect. Policy*. <https://doi.org/10.1002/aep.13468>.
- d’Andrimont, R., Verhegghen, A., Lemoine, G., Kempeneers, P., Meroni, M., Van Der Velde, M., 2021. From parcel to continental scale—A first European crop type map based on Sentinel-1 and LUCAS Copernicus in-situ observations. *Remote Sens. Environ.* 266, 112708. <https://doi.org/10.1016/j.rse.2021.112708>.
- Dai, K., Cheng, C., Kan, S., Li, Y., Liu, K., Wu, X., 2024. Impact of arable land abandonment on crop production losses in Ukraine during the armed conflict. *Remote Sens. (Basel)* 16 (22), 4207. <https://doi.org/10.3390/rs16224207>.
- Deininger, K., Ali, D.A., Kussul, N., Shelestov, A., Lemoine, G., Yailimova, H., 2023. Quantifying war-induced crop losses in Ukraine in near real time to strengthen local and global food security. *Food Policy* 115, 102418. <https://doi.org/10.1016/j.foodpol.2023.102418>.
- Devadoss, S., Ridley, W., 2024. Impacts of the Russian invasion of Ukraine on the global wheat market. *World Dev.* 173, 106396. <https://doi.org/10.1016/j.worlddev.2023.106396>.
- Dodd, E., Welsh, C., Joseph Glauber, J., 2024. Setting the Record Straight on Ukraine’s Grain Exports. <https://www.csis.org/analysis/setting-record-straight-ukraines-grain-exports> (accessed 30 September 2024).
- Estel, S., Kummerle, T., Alcántara, C., Levers, C., Prishchepov, A., Hostert, P., 2015. Mapping farmland abandonment and recultivation across Europe using MODIS NDVI time series. *Remote Sens. Environ.* 163, 312–325. <https://www.sciencedirect.com/science/article/pii/S003442571500125X>.

- Filippini, F., 2019. Sentinel-1 GRD preprocessing workflow. In Proceedings. 18, 1, 11. MDPI. doi: 10.3390/ECRS-3-06201.
- Hartman, I., Bilyash, B., Getman, A.P., Yaroshenko, O.M., Anisimova, H.V., 2024. Impacts of war on Ukrainian nature. *Int. J. Environ. Stud.* 81 (1), 455–462. <https://doi.org/10.1080/00207233.2024.2314856>.
- Glauber, J.W., Laborde Debucquet, D., 2023. The Russia-Ukraine conflict and global food security. *Int. Food Policy Res. Inst.* 187.
- Hairani Hairani, H., Dadang Priyanto, D.P., 2023. A new approach of hybrid sampling SMOTE and ENN to the accuracy of machine learning methods on unbalanced diabetes disease data. *Int. J. Adv. Comput. Sci. Appl.* 14 (8), 585–890.
- Hara, K., Saito, D., Shouno, H., 2015. Analysis of function of rectified linear unit used in deep learning. In: 2015 International Joint Conference on Neural Networks (IJCNN). <https://doi.org/10.1109/IJCNN.2015.7280578>.
- He, T., Zhang, M., Xiao, W., Zhai, G., Wang, Y., Guo, A., Wu, C., 2023. Quantitative analysis of abandonment and grain production loss under armed conflict in Ukraine. *J. Clean. Prod.* 412, 137367. <https://doi.org/10.1016/j.jclepro.2023.137367>.
- Ihle, R., Bar-Nahum, Z., Nivievskiy, O., Rubin, O.D., 2022. Russia's invasion of Ukraine increased the synchronisation of global commodity prices. *Aust. J. Agric. Resour. Econ.* 66 (4), 775–796. <https://doi.org/10.1111/1467-8489.12496>.
- JECAM Guidelines for cropland and crop type definition and field data collection. https://jecam.org/wp-content/uploads/2018/10/JECAM_Guidelines_for_Field_Data_Collection_v1_0.pdf (accessed 30 September 2024).
- Júnior, R.D.S.N., Ewert, F., Webber, H., Martre, P., Hertel, T.W., van Ittersum, M.K., Asseng, S., 2022. Needed global wheat stock and crop management in response to the war in Ukraine. *Glob. Food Sec.* 35, 100662. <https://doi.org/10.1016/j.gfs.2022.100662>.
- Kramer, O., 2016. Machine learning for evolution strategies, pp. 45–53. doi: 10.1007/978-3-319-33383-0.
- Kussul, N., Drozd, S., Yailymova, H., Shelestov, A., Lemoine, G., Deininger, K., 2023a. Assessing damage to agricultural fields from military actions in Ukraine: an integrated approach using statistical indicators and machine learning. *Int. J. Appl. Earth Obs. Geoinf.* 125, 103562. <https://doi.org/10.1016/j.jag.2023.103562>.
- Kussul, N., Shelestov, A., Yailymov, B., 2023b. Cloud platforms and technologies for big satellite data processing. *Lect. Notes Netw. Syst.* 809, 303–321. https://doi.org/10.1007/978-3-031-46880-3_19.
- Kussul, N., Shelestov, A., Yailymov, B., Yailymova, H., 2022. Analysis of cultivated areas in Ukraine during the war. In: 2022 12th International Conference on Dependable Systems, Services and Technologies (DESSERT). <https://doi.org/10.1109/DESSERT58054.2022.10018813>.
- Kussul, N., Shelestov, A., Yailymova, H., Yailymov, B., Lavreniuk, M., Ilyashenko, M., 2020. Satellite agricultural monitoring in Ukraine at country level: World Bank project. In: IGARSS 2020-2020 IEEE International Geoscience and Remote Sensing Symposium. IEEE, pp. 1050–1053. doi: 10.1109/IGARSS39084.2020.9324573.
- Kussul, N., Shelestov, A., Lavreniuk, M., Kolotii, A., Vasiliev, V., 2019. Transparent Land Governance in Ukraine within World Bank Program. In: IEEE 2nd Ukraine Conference on Electrical and Computer Engineering (UKRCON), Lviv, Ukraine, 2019, pp. 1077–1080. doi: 10.1109/UKRCON.2019.8879771.
- Kussul, N., Lavreniuk, M., Shelestov, A., Skakun, S., 2018. Crop inventory at regional scale in Ukraine: developing in season and end of season crop maps with multi-temporal optical and SAR satellite imagery. *Eur. J. Remote Sens.* 51 (1), 627–636. <https://doi.org/10.1080/22797254.2018.1454265>.
- Kussul, N., Lavreniuk, M., Skakun, S., Shelestov, A., 2017. Deep learning classification of land cover and crop types using remote sensing data. *IEEE Geosci. Remote Sens. Lett.* 14 (5), 778–782. <https://doi.org/10.1109/LGRS.2017.2681128>.
- Kussul, N., Lemoine, G., Gallego, F., Skakun, S., Lavreniuk, M., Shelestov, A., 2016. Parcel-based crop classification in Ukraine using Landsat-8 data and Sentinel-1A data. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* 9 (6), 2500–2508. <https://doi.org/10.1109/JSTARS.2016.2560141>.
- Kussul, N., Skakun, S., Shelestov, A., Kussul, O., 2014. The use of satellite SAR imagery to crop classification in Ukraine within JECAM project. In: 2014 IEEE Geoscience and Remote Sensing Symposium, pp. 1497–1500. <https://doi.org/10.1109/IGARSS.2014.6946721>.
- Kuzin, V., Musial, J., Shelestov, A., 2022. EO4UA initiative: scientific European support of Ukrainian scientific community. In: 2022 12th International Conference on Dependable Systems, Services and Technologies (DESSERT). <https://doi.org/10.1109/DESSERT58054.2022.10018706>.
- Leal Filho, W., Fedoruk, M., Eustachio, P.P., Barbir, J., Lisovska, T., Lingos, A., Baars, C., 2023. How the war in Ukraine affects food security. *Foods* 12 (21), 3996. <https://doi.org/10.3390/foods12213996>.
- Lemoine, G., 2023. Testing robustness of country-wide synoptic crop area estimates using machine learning techniques applied in the Ukraine war impact assessment. In: International Conference on Agricultural Statistics (ICAS IX): May 17 to 19, 2023, Washington, DC, United States.
- Li, H., Song, W., 2023. Spatial transformation of changes in global cultivated land. *Sci. Total Environ.* 859, 160194. <https://doi.org/10.1016/j.scitotenv.2022.160194>.
- Lin, F., Li, X., Jia, N., Feng, F., Huang, H., Huang, J., Song, X.P., 2023. The impact of Russia-Ukraine conflict on global food security. *Glob. Food Sec.* 36, 100661. <https://doi.org/10.1016/j.gfs.2022.100661>.
- Ma, Y., Lyu, D., Sun, K., Li, S., Zhu, B., Zhao, R., Song, K., 2022. Spatiotemporal analysis and war impact assessment of agricultural land in Ukraine using RS and GIS technology. *Land* 11 (10), 1810. <https://doi.org/10.3390/land11101810>.
- Matsala, M., Odruzhenko, A., Hinchuk, et al., 2024. War drives forest fire risks and highlights the need for more ecologically-sound forest management in post-war Ukraine. *Sci. Rep.* 14 (1), 4131. <https://doi.org/10.1038/s41598-024-54811-5>.
- Matsala, M., Odruzhenko, A., Sydorenko, S., Sydorenko, S., 2025. War threatens 18 % of protective plantations in eastern agroforestry region of Ukraine. *For. Ecol. Manage.* 578, 122361. <https://doi.org/10.1016/j.foreco.2024.122361>.
- Myroniuk, V., Weinreich, A., von Dosky, V., Melnychenko, V., Shumrai, A., Matsala, M., Gregory, M.J., Bell, D.M., Davis, R., 2024. Nationwide remote sensing framework for forest resource assessment in war-affected Ukraine. *For. Ecol. Manage.* 569, 122156. <https://doi.org/10.1016/j.foreco.2024.122156>.
- Pereira, P., Bašić, F., Bogunovic, I., Barcelo, D., 2022a. Russian-Ukrainian war impacts the total environment. *Sci. Total Environ.* 837, 155865. <https://doi.org/10.1016/j.scitotenv.2022.155865>.
- Pereira, P., Zhao, W., Symochko, L., Inacio, M., Bogunovic, I., Barcelo, D., 2022b. The Russian-Ukrainian armed conflict will push back the sustainable development goals. *Geogr. Sustain.* 3 (3), 277–287. <https://doi.org/10.1016/j.geosus.2022.09.003>.
- Potapov, P., Hansen, M.C., Pickens, A., Hernandez-Serna, A., Tyukavina, A., Turubanova, S., Zalles, V., Li, X., Khan, A., Stolle, F., Harris, N., Song, X.-P., Baggett, A., Kommareddy, I., Kommareddy, A., 2022. The global 2000-2020 land cover and land use change dataset derived from the Landsat archive: first results. *Front. Remote Sens.* <https://doi.org/10.3389/frsen.2022.856903>.
- Potapov, P., Hansen, M.C., Kommareddy, I., Kommareddy, A., Turubanova, S., Pickens, A., Adusei, B., Tyukavina, A., Ying, Q., 2020. Landsat analysis ready data for global land cover and land cover change mapping. *Remote Sens.* 12, 426. <https://doi.org/10.3390/rs12030426>.
- Prymak, I.D., Yeshchenko, V.O., Manko, Yu.P., 2008. Crop rotations in agriculture of Ukraine. K: Kvits, 208, 288 p. (in Ukrainian). <https://rep.btsau.edu.ua/bitstream/BNAU/11397/1/%D0%A1%D1%96%D0%B2%D0%BE%D0%B7%D0%BC%D1%96%D0%BD%D0%B8%D0%B2%D0%B7%D0%B5%D0%BC%D0%BB%D0%B5%D1%80%D0%BE%D0%B1%D1%81%D1%82%D0%B2%D1%96%D0%A3%D0%BA%D1%80%D0%B0%D1%97%D0%BD%D0%B8.pdf>.
- Qadir, A., Skakun, S., Becker-Reshef, I., Kussul, N., Shelestov, A., 2024. Estimation of sunflower planted areas in Ukraine during full-scale Russian invasion: insights from Sentinel-1 SAR data. *Sci. Remote Sens.* 10, 100139. <https://doi.org/10.1016/j.srs.2024.100139>.
- Rosa, L., Ragetti, S., Sinha, R., Zhovtonog, O., Yu, W., Karimi, P., 2024. Regional irrigation expansion can support climate-resilient crop production in post-invasion Ukraine. *Nat. Food* 5 (8), 684–692. <https://doi.org/10.1038/s43016-024-01017-7>.
- Shelestov, A., Siemens, E., 2022. OCRE project: consortium, main goals, approaches and opportunities. In: 12th International Conference on Dependable Systems, Services and Technologies (DESSERT). <https://doi.org/10.1109/DESSERT58054.2022.10018772>.
- Shelestov, A., Yailymov, B., Yailymova, H., Nosok, S., Piven, O., 2021. Cloud-based technologies for data processing in Ukraine: international context. In: International Scientific and Technical Conference-Modern Challenges in Telecommunications, pp. 101–118. https://doi.org/10.1007/978-3-031-16368-5_5.
- Shelestov, A., Lavreniuk, M., Vasiliev, V., Shumilo, L., Kolotii, A., Yailymov, B., Kussul, N., 2020. Cloud approach to automated crop classification using Sentinel-1 imagery. *IEEE Trans. Big Data* 6 (3), 572–582. <https://doi.org/10.1109/TBDATA.2019.2940237>.
- Shelestov, A., Lavreniuk, M., Kussul, N., Novikov, A., Skakun, S., 2017a. Large scale crop classification using Google earth engine platform. In: 2017 IEEE international geoscience and remote sensing symposium (IGARSS). IEEE, pp. 3696–3699. doi: 10.1109/IGARSS.2017.8127801.
- Shelestov, A., Lavreniuk, M., Kussul, N., Novikov, A., Skakun, S., 2017b. Exploring Google Earth Engine platform for big data processing: classification of multi-temporal satellite imagery for crop mapping. *Front. Earth Sci.* 5, 17. <https://doi.org/10.3389/feart.2017.00017>.
- Shumilo, L., Skakun, S., Gore, M.L., et al., 2023. Conservation policies and management in the Ukrainian Emerald Network have maintained reforestation rate despite the war. *Commun. Earth Environ.* 4 (1), 443. <https://doi.org/10.1038/s43247-023-01099-4>.
- Skakun, S., Abys, C., Adegbenro, M., et al., 2022. High-Impact Hot Spots of Land Cover Land Use Change in Ukraine. In: 2022 12th International Conference on Dependable Systems, Services and Technologies (DESSERT). <https://doi.org/10.1109/DESSERT58054.2022.10018657>.
- Skakun, S., Justice, C.O., Kussul, N., Shelestov, A., Lavreniuk, M., 2019. Satellite data reveal cropland losses in South-Eastern Ukraine under military conflict. *Front. Earth Sci.* 7, 305. <https://doi.org/10.3389/feart.2019.00305>.
- Solokha, M., Pereira, P., Symochko, L., Vynokurova, N., Demyanyuk, O., Sementsova, K., Barcelo, D., 2023. Russian-Ukrainian war impacts on the environment. Evidence from the field on soil properties and remote sensing. *Sci. Total Environ.* 902, 166122. <https://doi.org/10.1016/j.scitotenv.2023.166122>.
- Wagner, J., Becker-Reshef, I., Nair, S., Skakun, S., Sadeh, Y., Baber, S., Nerry, F., 2023. In-season progressive crop type mapping in war affected Ukraine. pp. EGU-16685. In: In egu General Assembly Conference Abstracts. <https://doi.org/10.5194/egusphere-egu23-16685>.
- Welsh, C., Dodd, E., 2022. Rebuilding Ukraine's Agriculture Sector: Emerging Priorities. <https://www.csis.org/analysis/rebuilding-ukraines-agriculture-sector-emerging-priorities> (accessed 22 November 2024).
- Welsh, C., Glauber, J., 2024. Center for Strategic and International Studies (CSIS), 2022. Food as the "Silent Weapon": Russia's Gains and Ukraine's Losses. <https://www.csis.org/analysis/food-silent-weapon-russias-gains-and-ukraines-losses> (accessed 30 September 2024).
- World economic forum, 2024. Ukraine's food exports by the numbers. <https://www.weforum.org/agenda/2022/07/ukraine-s-food-exports-by-the-numbers/> (accessed 30 September 2024).

United States Department of Agriculture (USDA), 2024. Ukraine: Grain and Feed Annual. <https://fas.usda.gov/data/ukraine-grain-and-feed-annual-7> (accessed 30 September 2024).

Van Tricht, K., et al., 2023. WorldCereal: a dynamic open-source system for global-scale, seasonal, and reproducible crop and irrigation mapping. *Earth Syst. Sci. Data* 15 (12), 5491–5515. <https://doi.org/10.5194/essd-15-5491-2023>.

Waldner, F., Bellemans, N., Hochman, Z., et al., 2019. Roadside collection of training data for cropland mapping is viable when environmental and management gradients are surveyed. *Int. J. Appl. Earth Obs. Geoinf.* 80, 82–93. <https://doi.org/10.1016/j.jag.2019.01.002>.

World Cereal project. <https://esa-worldcereal.org/en> (accessed 30 September 2024).