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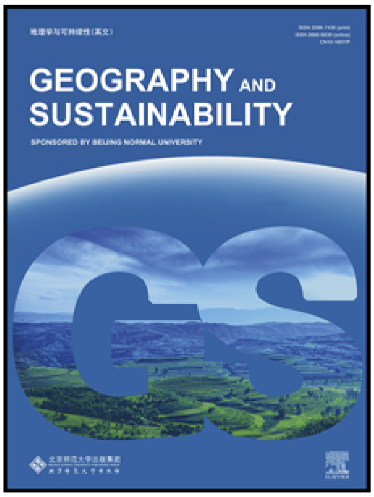

Planting area and production decreased for winter-triticeae crops but increased for rapeseed in Ukraine with climatic impacts dominating

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Highlights

- A new framework is proposed to map annual dynamics of crop area, yield simultaneously.
- Harvest area and production declined in 2022 for wheat but increased for rapeseed.
- Low precipitation explained yield variations of -1.3% and -4.2% for two crops in 2022.
- War conflict-related factor explained only -0.9% and -0.5% for yields in 2022.
- Study can serve as an early food security warning system for other areas and crops.

Planting area and production decreased for winter-triticeae crops but increased for rapeseed in Ukraine with climatic impacts dominating

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Abstract: On-time mapping dynamics of crop area, yield, and production is important for global food security. Such information, however, is often not available. Here, we used satellite information, a spectral-phenology integration approach for mapping crop area, and a machine learning model for predicting yield in the war-stricken Ukraine. We found that in Ukraine crop area and production declined in 2022 relative to 2017–2021 and 2021 for winter-triticeae crops, which was invaded before the cropping season in February of that year. At the same time, crop area and production for rapeseed increased in Ukraine, with yields consistently lower by 6.5% relative to 2021. The low precipitation and the Russian-Ukrainian conflict-related factors contributed to such yield variations by -1.3% and -0.9% for winter-triticeae crops and -4.2% and -0.5% for rapeseed in 2022. We demonstrate a robust framework for monitoring country-wide crop production dynamics in near real-time, serving as an early-food-security-warning system.

Keywords: Food security; Conflict; Machine learning; Production; Satellite

1. Introduction

Ukraine is one of the world's largest producers of grain with an agricultural area of 27.2 million ha of which 56% is for cereals and 24% for oilseed crops. The main cereal crops are wheat and maize, and the main oilseed crops are sunflower and rapeseed. Ukraine is one of the world's largest wheat producers with 3.2% of global production and 9.1% of global exports (Jagtap et al., 2022). Some low-income countries in North Africa and the Middle East, some European countries, as well as some of the most food-insecure countries such as Yemen, Sudan, and Bangladesh, rely heavily on agricultural exports from Ukraine (Bentley et al., 2022). For example, two-thirds of Egypt and Libya's wheat imports depend on Ukraine and Russia (Fig. S1). Ukraine is also a large producer of oilseed rape. On the world market, the share of Ukrainian rapeseed export is 14%–15%, and almost half of the European Union rapeseed oils imports come from Ukraine (Tarja, 2022). Therefore, influences of the Russian-Ukrainian conflict on food security have been of key concern to many (Mottaleb et al., 2022; Pörtner et al., 2022; Ukraine, 2022).

An armed conflict may reduce the capacity of food production systems directly by affecting producers, agricultural inputs, labor, machinery, and infrastructure. In combat areas, residual and undetonated ammunition and detonation craters constrained field access. It may also indirectly affect supply chains through food storage and transport, food price, purchasing power, economic sanctions, and food trade restrictions (Behnassi and El Haiba, 2022). Previous studies have explored the impact of the Russia-Ukraine conflict on food access and supply, as well as the role of international aid (Jagtap et al., 2024). They indicate that the conflict is causing significant disruptions to global food supply chains, particularly affecting countries that rely on exports from Ukraine and Russia and utilize the Red Sea route. Previous studies on the consequences to other countries of this conflict have focused mostly on the economy (Liadze et al., 2022; Mbah and Wasum, 2022). However, variations in the capacity of the food production system have seen little attention, maybe due to the challenges in quantifying the impacts of conflict at a high resoultion in real-time.

Access to accurate information on crop planting area, yield, and production is often limited, especially in conflict regions. Some studies have relied on administrative-level census data or household-level agricultural production surveys to quantify the changes in crop production (Blankespoor et al., 2020). This method is time-consuming, imprecise, and often hindered by conflict. Remote sensing and machine learning are the state-of-the-art approaches to map crop planting area and yield at a grid scale, however, very few studies have applied them to estimate the grid-specific yield of different crops during the Russia-Ukraine conflict. Previous studies have assessed food loss during the Russia-Ukraine war (Mottaleb et al., 2022), but typically used descriptive methods (Chen et al., 2024), used satellite-based vegetation indices as proxies (Deininger et al., 2022) or relied on arbitrary assumptions (Chen et al., 2024). Crop yields can be derived from changes in the Normalized Difference Vegetation Index (NDVI) maxima from remote sensing. Although NDVI senses vegetation greenness and has been widely used as a proxy for monitoring crop biomass growth, it fails to accurately estimate yields due to an inconsistent correlation between growth and final yield (Mkhabela et al., 2011). Furthermore, previous studies have not disentangled the roles of climate variability and war in crop yield change.

To fill these knowledge gaps, we develop a comprehensive Crop Production Mapping Framework (CPMF). CPMF utilizes satellite imagery and data-driven models to map crop area and yield, enabling a spatially gridded assessment of agricultural losses during the Russia-Ukraine conflict. A spectral-phenology integration approach for mapping crop area and a machine learning (ML)-based grid yield prediction approach was established. Integrating satellite imagery with ML can provide additional dynamic information on crop yield development and improve yield estimates. The state-of-the-art methods have not been applied into a country suffering from a war, although it is powerful to provide critical information for famine early warning systems. CPMF can map crop planting areas and yield dynamics in a scalable manner, reflecting the spatial differences in crop production information. Additionally, CPMF can disentangle the contributions of climate and war-related factors to yield changes. CPMF can provide on-time information and serve as an early food security warning system in conflict regions. Using CPMF, we investigate the annual dynamics of crop area, yield, and production of two major winter crops in Ukraine (i.e., winter-triticeae crops and rapeseed) compared with the historical reference period 2011 to 2022, and attribute causes to detected changes.

2. Materials and methods

Here, we develop a novel framework to analyze annual dynamics of crop production (inlcuding crop planting area and final yield) and disentangle quantitatively the contribution of climatic and conflict factors to yield variability in Ukaine, taking winter-triticeae crops and rapeseed as examples (Fig. 1).

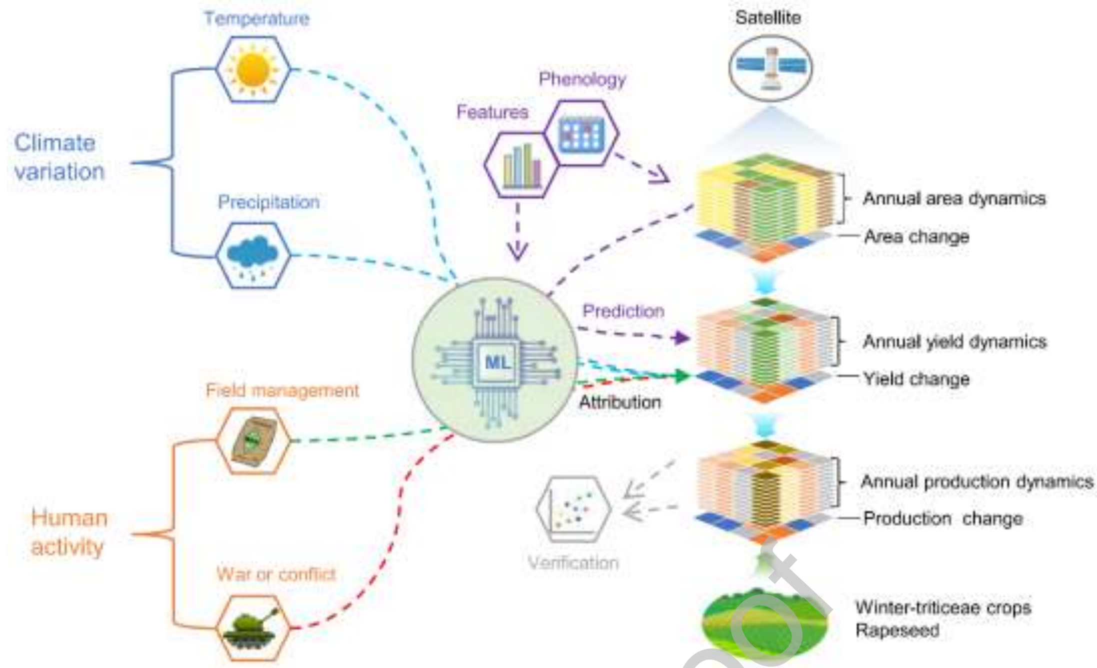

Fig. 1. The framework for mapping crop planting area and production and crop production variation attribution.

2.1 Studied areas

As the second-largest country in Europe after Russia, Ukraine is located in Eastern Europe, bordering Russia in the northeast and east. The territory covers an area of 600,000 km², with main landscapes of plains and plateaus. Ukraine is divided into 25 subnational administrative units (*source*: The Global Administrative Unit Layers 2015, https://data.apps.fao.org/catalog/dataset/9648080c-5ac0-4089-9b83-3f04261c36b6). The country is rich in natural resources, especially for the very fertile "black earth", known as Chernozem, which is also the main reason why Ukraine is known as the "Breadbasket of Europe". Its primary soil types include Chernozem, which accounts for about 60% of the country and is mainly in the central and southern regions, making it one of the most fertile soils in the world, and Brown Earth, which accounts for about 20% and is primarily distributed in the western regions (*source*: Legacy Soil Maps and Soils Databases, https://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/en/). Ukraine is a major agricultural producer globally, being one of the largest exporters of wheat and barley. The main crops include wheat, maize, barley, and rapeseed, with wheat cultivated in about 38% of the total arable land in 2021, followed by maize (30%), barley (15%), and rapeseed (about 7%) (*source*: FAOSTAT, https://www.fao.org/faostat/en/#data/QCL).

2.2 Data

Satellite data. We used the MOD09A1 surface spectral reflectance from the Moderate Resolution Imaging Spectroradiometer (MODIS) for 2010–2022 with 500 m resolution and 8-day composite. MODIS images with dense time series have been widely used for mapping crop maps and monitoring crop growth. We used Quality Assessment (QA) bands to remove cloud and shadow pixels to obtain clear cloud-free images. We calculated the enhanced vegetation index (EVI). EVI is less saturated than the normalized vegetation index (NDVI) for dense vegetation canopy, and it has been widely used as a proxy for vegetation productivity (Eklund et al., 2017). In addition, we calculated the Difference Yellowness Index (DYI) and Enhanced Difference Yellowness Index (EDYI) for capturing yellow flowers and drought vegetation indices (Sulik and Long, 2016; Zang et al., 2020) (Supplementary Text S1). We also collected day and night land surface temperature (LST) data from the MOD11A2 product for 2010–2022 with 1000 m resolution and 8-day composite. We used nighttime light (NTL) as proxy data for analyzing the intensity of human activities(Li et al., 2022). NTL with a spatial resolution of 15 arcsec for 2014–2022 was collected from monthly averaged radiance synthetic images from the Visible Infrared Imaging Radiometer Suite (VIIRS). Missing year data were replaced with the most recent later year. The satellite datasets were collected and processed through the google earth engine (GEE) cloud computing platform (Gorelick et al., 2017). We resampled all raster data to 500 m resolution using the nearest neighbor method.

Conflict data. The geo-referenced conflict dataset for Ukraine comes from the Armed Conflict Location & Event Data Project (ACLED) (Raleigh et al., 2010). ACLED is one of the most comprehensive datasets for conflict research (Anderson et al., 2021;

Olsen et al., 2021). We collected all conflict events (8,701) in Ukraine from February 2022 to May 2022. We obtained the spatial pattern of conflict point density in Ukraine using ArcGIS software. We found a significant relationship between conflict point density and changes in NTL between 2017–2021 and 2022 (Fig. S2).

Climate data. We used the ERA5-Land Monthly Averaged reanalysis dataset from the European Centre for Medium-Range Weather Forecasts (ECMWF)(Copernicus Climate Change Service, 2019). ERA5-Land has a higher spatial resolution (~11,132m) than ERA5. We collected the monthly air temperature at 2 m, precipitation, atmospheric pressure, solar shortwave radiation, volumetric of soil water content, and soil temperature for 2010–2022. Compared with other meteorological data products, ERA5-Land has higher spatial resolution and timeliness.

Soil data. We obtained the data on soil properties and soil texture from the Harmonized World Soil Database (HWSD) with a spatial resolution of 30 arc sec (FAO and ISRIC, 2012). The soil properties include organic carbon, pH, and bulk density, while the soil texture encompasses gravel, clay, silt, sand, and fractions of soil sodicity in the topsoil layer (0–30 cm). We resampled the raster data to a resolution of 500 m using the nearest neighbor method.

Landcover. We used the annual land cover product (MCD12Q1) derived from MODIS with a 500 m resolution from 2011 to 2020. It is a product based on supervised classification (Sulla-Menashe and Friedl, 2018). We extracted all cropland areas from the International Geosphere-Biosphere Programme (GBP) classification scheme. Missing year data were replaced with the most recent previous year.

Agricultural statistics. Agricultural statistics including the harvested area of crops, yields, and production were collected from the state statistics service of Ukraine for 2011–2021 for the administrative divisions of Ukraine at the first level (autonomous republic, cities with special status, and oblasts).

Administrative boundary. The administrative boundaries of Ukraine were collected from the Global Administrative Areas (GADM).

2.3 Crop classification

Winter-triticeae crops, maize, sunflower, and rapeseed are the main crops in Ukraine. Winter-triticeae crops and rapeseed are Ukraine's main winter crops, usually sown from September to October and harvested from July to August (Mustafa, 2022). Spring wheat and spring rapeseed account for only 3% of the total wheat and rapeseed area. Summer crops (e.g., maize and sunflower) are usually sown in April and harvested from September to October.

We mapped winter rapeseed based on phenological information and flowering characteristics. We first used the cropland layer from MCD12Q2 as a cropland mask. Rapeseed and sunflower are the two oilseed crops in Ukraine with dense petal canopies during flowering. Yellow petals increased the red reflectance and green reflectance (Sulik and Long, 2016). The DYI during the flowering of rapeseed and sunflower shows significant peaks (Zang et al., 2020), which are much higher than for other vegetation types (Fig. S3). There were significant differences in the timing of the flowering period between winter rapeseed (April to May) and sunflower (July to August), which were used to differentiate the two crops. In addition, EDYI and EVI reached the maximum at the flowering period of rapeseed (Fig. S4). We calculated the maximum values (EVImax, DYImax, EDYImax) of EVI, DYI, and EDYI during the rapeseed flowering period, respectively. Pixels with EVImax $\geqslant$ 0.4, DYImax $\geqslant$ 0.06, and EDYImax $\geqslant$ 0.01 were classified as rapeseed (Figs. S3–S4). The histogram of rapeseed samples determined the threshold of the indices. The rapeseed samples were selected by high spatial resolution Sentinel-1/2 according to the method of Han et al. (2021). Finally, we generated winter rapeseed annual harvested area for the period 2011–2022 (Fig. S5).

Distinct phenological characteristics of the EVI temporal profiles were used to discriminate between winter wheat and other crops (Luo et al., 2022). First, the timing of the critical phenological phases for winter-triticeae crops was generally earlier than spring barley and summer crops (e.g., maize and millet) (referenced crop calendar for Ukraine from https://ipad.fas.usda.gov/rssiws/al/crop_calendar/umb.aspx). Moreover, winter-triticeae crops has a much longer growth period than spring and summer crops. We first used the cropland layer from MCD12Q2 as a cropland mask. Then, we applied the Savitzky-Golay filtering method to reconstruct the EVI time series (Chen et al., 2004). More specifically, the time-specific window (Win_{max}) of winter-triticeae crops heading was determined based on crop calendar data and varied across different regions. For example, Win_{max} was defined as a time window ranging from mid-May to early June for Southern Ukraine. In addition, we defined 35% for a drop of at least EVI_{decr}% during 40 days in order to detect the time of senescence of winter-triticeae crops. Then, we masked out rapeseed pixels from the annual winter-triticeae crops map to improve the accuracy of winter-triticeae crops mapping. Finally, we identified the annual spatial distribution of winter-triticeae crops during 2011–2022 (Fig. S6).

We compared the classification results for winter-triticeae crops and rapeseed with available agricultural statistics from 2011 to 2021. The results showed that the classified area of winter-triticeae crops and rapeseed had a significant linear relationship with agricultural statistics. The mean coefficient of determination (R^2) was 0.67 and 0.79 for winter-triticeae crops and rapeseed, respectively, from 2011 to 2021 (Table S1).

2.4 Yield prediction

We constructed ML models for gridded yield prediction of winter-triticeae crops and rapeseed using the Long Short-Term Memory (LSTM) and Gaussian process regression (GPR) respectively. The LSTM and GPR algorithms were developed using Python (TensorFlow) and MATLAB software (Version: R2022b). We selected monthly features including climate, vegetation index, reflectance, and soil data for the growing season of winter-triticeae crops and winter rapeseed. Details of the features can be found in Supplementary Text S1-2. We also used NTL as a feature because NTL indicates the intensity of human activities (Levin et al., 2020). The change in NTL during the conflict can be used as a proxy for the impact of the conflict (Li et al., 2018, 2022; Zheng et al., 2022) (Fig. S2). Note that the change in NTL during the conflict reflects factors other than the conflict, including the economic and urban development of Ukraine. The change in NTL is currently the best conflict-related factors (CRF) proxy data we can collect for spatial grids with long time series. Features were aggregated to months using the monthly maximum and average. All features were masked using winter-triticeae crops and rapeseed maps for each year. We used a "set aside one-year" strategy to eliminate temporal autocorrelation between samples. We tested the ML model with one year's data and trained the ML model with the remaining years' data. Specifically, we recursively selected each year from 2011 to 2021 for testing and the remaining years for training. The mean R^2 was 0.73 and 0.62 for winter-triticeae crops and rapeseed models from 2011 to 2021, respectively (Table S2). For example, we trained the models with data from 2011 to 2020 and optimized the parameters, evaluated the training accuracy of the models using cross-validation, and tested the models using data from 2021. Also, we used a "set aside one-region" strategy to eliminate spatial autocorrelation between samples. We tested the ML model with one region's data and trained the ML model with the remaining regions' data. The mean R^2 was 0.72 and 0.66 for winter-triticeae crops and rapeseed models for all regions, respectively. For example, we trained the models with data from other regions excluding Khmelnitsky and optimized the parameters, evaluated the training accuracy of the models using cross-validation, and tested the models using data from Khmelnytskyi. The results show that the average prediction accuracy of winter-triticeae crops and rapeseed yields based on the "set aside one-year" strategy is similar to that of the "set aside one-region" strategy. In addition, the average prediction accuracy of LSTM (R^2=0.56) for rapeseed yield was lower than that of GPR (R^2=0.66). Therefore, we used GPR to predict rapeseed yield. Finally, each optimized model was used to estimate the grid yield for the test years (Figs. S7–S8). Details of the ML models for predicting winter-triticeae crops and rapeseed yields can be found in Supplementary Text S2 and Fig. S9.

We aggregated simulated winter-triticeae crops and rapeseed grid yields to administrative units and compared them with agricultural statistics from the state statistics service of Ukraine. The mean R^2 (RMSE) for winter-triticeae crops and rapeseed grid yields from 2011 to 2021 were 0.76 (525.20 kg/ha) and 0.60 (423.77 kg/ha), respectively (Table S3). The annual winter-triticeae crops and rapeseed grid production was obtained by multiplying the yield by the area in each grid (Figs. S10–S11). The results showed that the mean R^2 for the production of winter-triticeae crops and rapeseed were 0.60 and 0.78 from 2011 to 2021, respectively (Table S4).

2.5 Disentangling the roles of climate variability and CRF in crop yield variations

We trained all ML yield prediction models using data from 2011 to 2021. Then, we used these trained models to predict winter-triticeae crops and rapeseed grid yields in 2022. We conducted factorial simulations experiments to evaluate the relative contributions of precipitation (all months during the growing season) and CRF to yield prediction in winter-triticeae crops and rapeseed at the subnational level in 2022 (Table S5). As Yuan et al. (2019), in the first simulated experiment (MLall), all the features in 2022 were set to vary over time to examine yield response to all environmental changes. In the second simulation experiment (MLpre and MLcrf), one feature in 2022 was held constant at the initial baseline value (the mean value for 2017–2021), and the other features were set to vary over time. For example, the precipitation feature in the MLpre simulation experiment was held constant at the mean value for 2017–2021, allowing all other features to change over time from 2017 to 2022. We consider the differences between the simulation results of MLall and MLpre, and MLall and MLcrf, to estimate the relative contributions of Pre and CRF to winter-triticeae crops and rapeseed yield prediction in 2022.

3. Results

3.1 Dynamics of winter-triticeae crops and rapeseed area

Satellite observations show that the maximum area extent of winter-triticeae crops and rapeseed in Ukraine from 2011 to 2022 was 3.5×10^7 ha and 7.4×10^6 ha (Fig. S12), respectively. Winter-triticeae crops is mainly distributed in eastern Ukraine (Fig. 2(a)–(b)), with the largest area in Dnipropetrovsk, Odesa, and Zaporizhzhia, close to the ongoing combat zones. Rapeseed is mainly distributed in the west and south (Fig. 2(d)–(e)), with the largest area in Odessa, Vinnytsia, and Khmelnytskyi, further separated from active combat than the main winter-triticeae crops-growing regions. Most of the northwest (Volyn) and southwest (Transcarpathia) are covered by forests (Fig. S13). Compared to the average over 2017–2021 (Fig. 2(b)), winter-triticeae crops area decreased by 12% as a whole in 2022 (Fig. 3(a)), which decreased in western and eastern Ukraine but increased in central Ukraine (Fig. 2(c)). The rapeseed area in 2022 was 1.1×10^6 ha (Fig. 2(d)), 23% higher than the average over 2017–2021 (Figs. 2(e), 3(a)), especially in Dnipropetrovsk, Kherson, Mykolaiv, and Zaporizhzhia in southeastern Ukraine (Fig. 2(f)). Compared to 2021, winter-triticeae crops area decreased by 13% as a whole in 2022 (Fig. 3(a), Fig. S14(a)–(c)). The rapeseed area increased by 12%, especially in southeastern Ukraine (Fig. 3(b), Fig. S14(d)–(f)). In many grid cells winter-triticeae crops and rapeseed showed greater than 30% area changes, which were mainly due to crop rotation patterns. In addition, the cropping frequency of rapeseed was lower than that of winter-triticeae crops because of rotational constraints (Fig. S12).

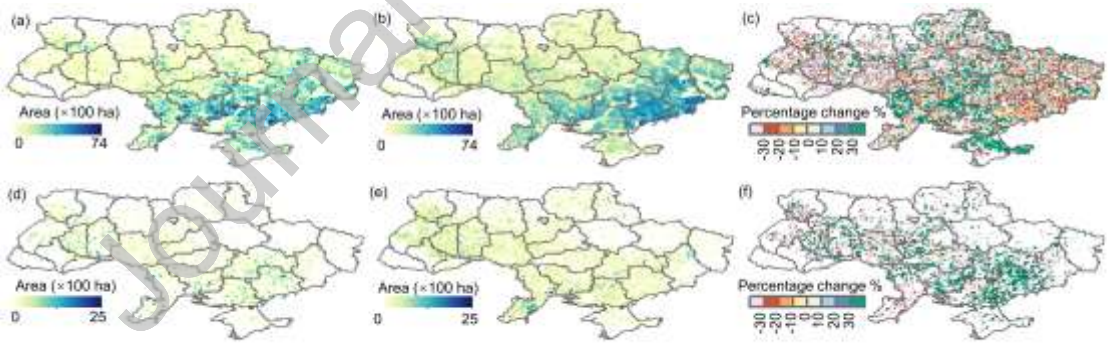

Fig. 2. Winter-triticeae crops and rapeseed area in Ukraine. Winter-triticeae crops (a) and rapeseed (d) area in 2022; their average areas in 2017–2021 (b, e); percentage change of their areas in 2022 relative to those in 2017–2021 (c, f), and the black dots for the areas in 2022 being larger than the maximum or less than the minimum in 2017–2021. Winter-triticeae crops (a–c), rapeseed (d–f).

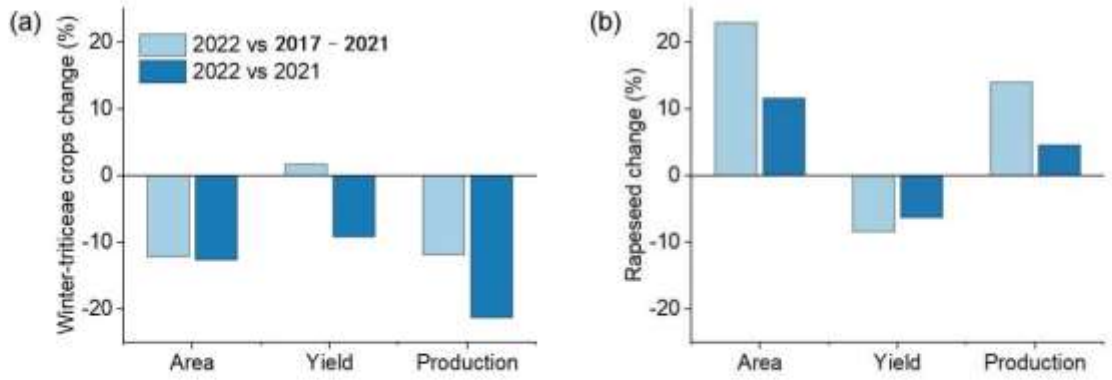

Fig. 3. Changes in the estimated area, yield, and production of winter-triticeae crops (a) and rapeseed (b) in 2022 compared with those in 2017–2021 (light blue) and 2021 (dark blue).

3.2 Dynamics of winter-triticeae crops and rapeseed yield and production

Crop yield estimates are more challenging than crop area estimates as various factors affect crop growth and productivity directly or indirectly during a growing period. The ML-based estimates show that winter-triticeae crops and rapeseed yields in Ukraine were on average 4.5 t/ha and 2.3 t/ha in 2022, varying by year and location. Winter-triticeae crops yields were relatively low in the east (Kherson 3.7 t/ha) and high in the west (Khmelnytskyi 5.6 t/ha) (Fig. 4(a)), which were lower in the south and east but higher in the north-central region in 2022 compared to the average over 2017–2021 (Fig. 4(b)–(c)). Winter-triticeae crops yield in 2022 in the center and north is greater than the maximum in 2017–2021. Mean winter-triticeae crops yield declined by 9% in 2022 relative to 2021 (Fig. 3(a), Fig. S15(a)–(c)). The spatial variations of rapeseed yield in 2022 were lower than the averages over 2017–2021 (Fig. 4(d)–(f)). Likewise, rapeseed yields in 2022 were 6% lower than those in 2021 (Fig. 3(b), Fig. S15(d)–(f)), which were relatively high in the northwestern parts of Ternopil, Rivne, and Vinnytsia.

The product of area and yield, crop production, indicated more change than those of yield or area separately. With the highest production in the eastern regions (Fig. 4(g)–(i)), winter-triticeae crops production in 2022 was lower than that in 2017–2021 (12%) and in 2021 (21%) (Fig. 3(a)), especially in the west and east. Rapeseed production in

2022 increased mainly in the eastern Dnipropetrovsk, Kherson, and Zaporizhzhia (Fig. 4(j)–(l)), compared to 2017–2021. The spatial patterns of winter-triticeae crops and rapeseed production were highly consistent with their respective sowing area (Fig. 2(c), (f); Fig. 4(i), (l)). Compared to 2021, rapeseed yields were lower but production was higher due to an increase in area in 2022 (Fig. 3(b), Fig. S15(j)–(l)). In many grid cells winter-triticeae crops and rapeseed showed greater than 30% production changes, mainly due to area variation caused by crop rotation patterns.

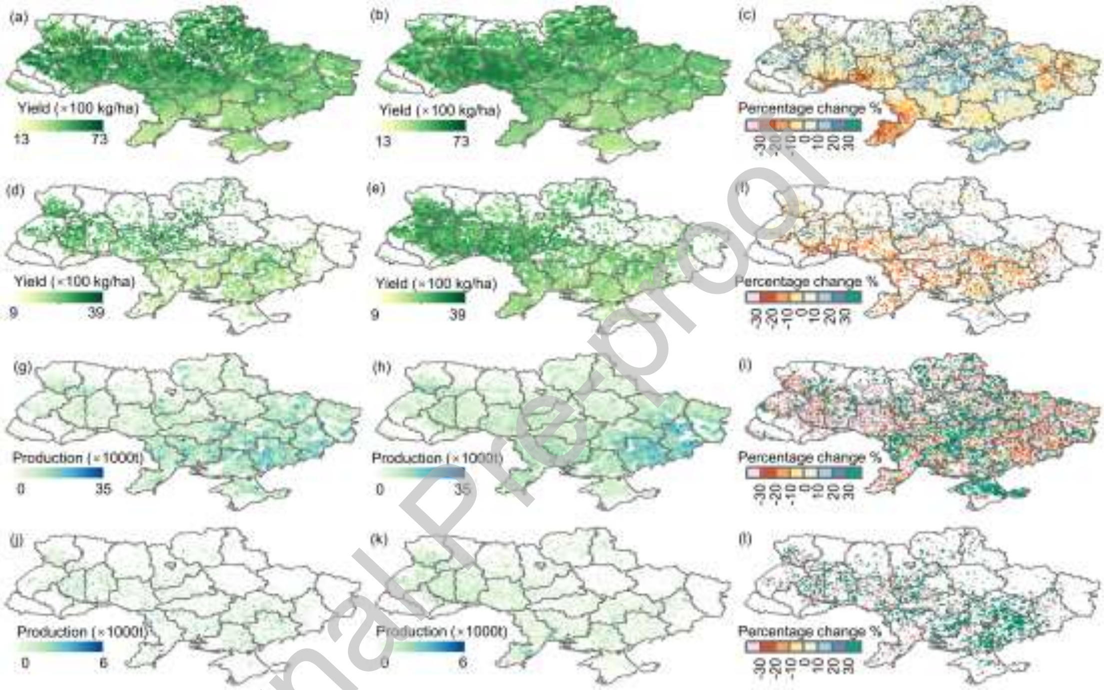

Fig. 4. Winter-triticeae crops and rapeseed yield and production, and their changes across Ukraine. (a), (d), (g), (j) Yield and production of winter-triticeae crops and rapeseed in 2022; (b), (e), (h), (k) their averages in 2017–2021; (c), (f), (i), (l) their changes in 2022 relative to 2017–2021, and black dots for the yield and production in 2022 being greater than the maximum or less than the minimum in 2017–2021. Winter-triticeae crops (a–c, g–i), rapeseed (d–f, j–l).

3.3 Dynamics of precipitation and conflict-related factors and their contributions to yield

We conduct factorial simulation experiments (see methods) to disentangle the relative contributions of precipitation and conflict-related factors (CRF) to winter-triticeae crops and rapeseed yields in 2022 at the subnational level. Temperature is excluded in the analyses because it changed insignificantly (Fig. S16(a)). Precipitation over the crop growing period differed significantly by -333 mm to 208 mm in 2022 from the average in 2017–2021, with precipitation increased in the north but decreased in the northwest and south (Fig. S16(b)). Changes in Nighttime light (NTL) from the Visible Infrared Imaging Radiometer Suite (VIIRS) were significantly associated with conflict point density (R^2=0.52, P<0.05) (Fig. S2). With economic development and population growth in Ukraine, NTL increased generally and reached a peak in 2021 (Fig. S17). However, NTL decreased by 30% in 2022 relative to 2021. NTL declined significantly in most of Ukraine, especially in the eastern parts (Fig. S2(a)). Curfews during conflict and the transfer of refugees were among the reasons for the decline in NTL (Scientific Centre for Aerospace Research of the Earth Institute of Geological Science National Academy of Sciences of Ukraine, Kyiv, Ukraine et al., 2022). This is because they reduce the use of artificial lighting and the movement of people at night. The changes in NTL directly can reveal the conflict impact on human activities (Li et al., 2018, 2022; Zheng et al., 2022), which are therefore used as a proxy for CRF from 2022 to 2021. Overall, CRF, and especially precipitation did affect yields negatively in 2022 (Fig. 5). Precipitation and CRF contributed to yield variations on average by -1.3% (-4.2%) and -0.9% (-0.5%) for winter-triticeae crops (rapeseed).

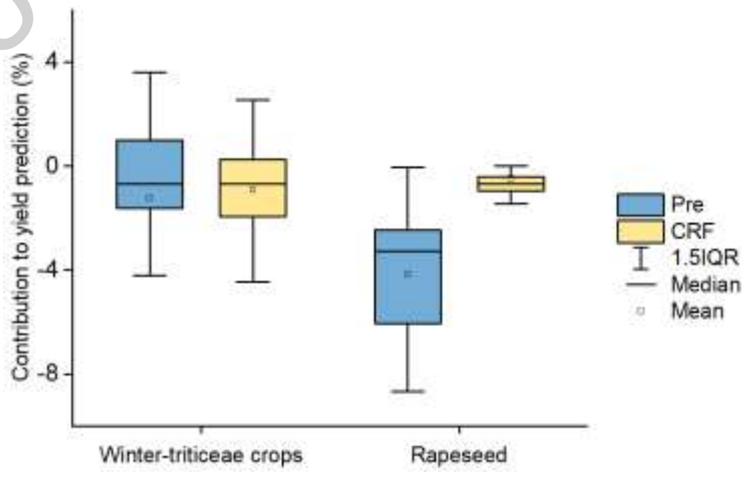

Fig. 5. Contributions of precipitation (Pre) and conflict-related factors (CRF) to yield variations at the subnational level for Ukraine in 2022.

4. Discussion

4.1 The singnificance of this study

This study demonstrates that combining satellite observations and crop phenology with an ML method can obtain the annual dynamics of crop area, yield, and production at 10km grid scale in near-real time. Comparing with many previous studies focused on planted areas or trade impacts from local war or conflict (e.g., Baumann and Kuemmerle, 2016; Behnassi and Haiba 2022), we quantitatively identified the intricate impacts from war conflict on crop yield. Winter-triticeae crops and rapeseed were sown in October 2021 before the beginning of the war in March 2022, consequently, the conflict would not impact their sowing areas. In the spring and summer of 2022, insufficient precipitation might affect negatively yield in most southern and western areas, although timely precipitation increased yield in some central and northern areas (Fig. S18). Our estimated impacts from precipitation are consistent with those from the JRC's MARS bulletin (European Commission. Joint Research Centre, 2022). Compared to the bulletin, we map the spatial patterns of yield and production of winter-triticeae crops and rapeseed in a long time series at the grid scale. Ukraine tried to take measures to ensure agricultural operations as much as possible (Mustafa, 2022).

Since the beginning of the Russia-Ukraine conflict, several studies have been published, including estimates of the impact of the conflict on agricultural land (Ma et al., 2022), wheat consumption and the intake of wheat calories and protein (Mottaleb et al., 2022), and global trade and food security (Zhou et al., 2023). However, these studies have rarely assessed systematically the spatiotemporal changes in crop area, yield, and production in Ukraine during the conflict, and the relative roles of climate variability and conflict. Some studies have assessed crop production losses in Ukraine, but based on statistical data (Pereira et al., 2022), relied on descriptive methods or using assumption scenarios (Nasir et al., 2022; Sun et al., 2022). In addition, NDVI changes are often used as proxies for yield changes (Chen et al., 2024; Deininger et al., 2022). Although NDVI can characterize vegetation growth status, its ability to estimate yield is limited (Mkhabela et al., 2011). Compared to previous studies, this study uses the state-of-the art approaches to estimate crop planting area and crop yield in real-time based on satellite imagery and ML instead of NDVI, providing more robust information on crop production dynamics at 10km resolution across the entire territory of Ukraine. Furthermore, for the first time, we disentangle the roles of climate variability and the Russia-Ukraine conflict in crop yield change.

4.2 Uncertainties and limitations

Although the dynamics of area, yield, and production have been obtained simultaneously, other factors need to be considered. For example, conflict might directly hinder agricultural activities such as field management and crop harvesting, however, identifying such activities from MODIS satellite images is still a challenge. It was reported that about 27.6% of planted wheat, rye, and barley areas were not harvested in 2022 in Ukraine (Mustafa, 2022). In addition, the conflict prevented the sowing activities for spring crops in 2022 (Sacks et al., 2010; Ukraine, 2022). Military operations have damaged land in the conflict areas and made some land inaccessible. Such temporary or permanent cropland abandonment might occur if the war would persist together with climate variations (Baumann and Kuemmerle, 2016; Olsen et al., 2021; Skakun et al., 2019). Longer war may affect sowing, labor availability, infrastructure, and agricultural management and harvesting, and consequently will inevitably impact all issues related to food production. Another challenge comes from economic sanctions and food trade restrictions from war conflict (Ben Hassen and El Bilali, 2022) (e.g. the increasing trade costs and timeliness of deliveries), such as the main fertilizer exporters from Russia and Belarus. Fertilizer supply disruption and logistics may further aggravate the adverse impacts on crop yields (Bentley et al., 2022). Restricting trade in these items, food transport, and export would cause larger uncertainty in global markets (e.g., price volatility) (Ben Hassen and El Bilali, 2022). Therefore, the integrated impacts of the war on food production and food security need to be further investigated if the war would persist. Moreover, agricultural information extracted through remote sensing images is influenced by the quality of MODIS data. Poor observations, based on number of pixels covered by cloud and shadow, during the winter crop growing period (October to July) reached 28% on average (Fig. S19). NTL was applied as a proxy for the impact of the conflict considering its significant associations with the density of conflict points (Fig. S2). It can be improved if more conflict data become available.

In this study, we aim to predict crop yield 1–2 months before harvest to assist managers in making agricultural policy adjustments in advance. Therefore, we selected the estimated conflict period from February to May as the predictor in our modeling. However, this approach has its limitations. Predicting crop yield before harvest may overlook the impact of war during the harvest period, which may affect harvest and potentially reduce the accuracy of the yield predictions. In further studies, a rolling prediction approach (Chen and Tao, 2022) should be applied to incorporate continuously newly available information in forecasting crop yield. Additionally, the DYI index during the flowering period of rapeseed and the regions affected by war may also influence the prediction skill and should be considered in further research.

4.3 Implications for management

A scientific decision is strongly depended on the detailed and accurate information collected. Food availability in a nation is main from crop production, especially during a conflict. It is worthwhile to investigate how to build an accurate and early warming food system integrating with multiple elements and regions and provides a good basis for related decision-makers. We find that the Russia-Ukraine conflict shows oppositve impacts on winter crop production in the first year, implying high necessarities for building an accurate bottom-up national food warming system. With the conflict persistence, more extra pressures from both decreases in cropland use and final yield due to less field management will worsen food insecurity. Thus, food-security-early-warning system for all countries, regions, and even globe remains an urgent issue, especially for a shock from conflict or extreme events in the world.

5. Conclusions

The Russia-Ukraine conflict endangers global food security. We develop an advanced framework that uses publicly available satellite data and data-driven methods to map crop areas and yield nationwide automatically in near real-time. This framework can further disentangle the contributions of climate variability and CRF to crop yield changes. We demonstrate the framework in providing crop production information during the Russia-Ukraine conflict at a grid scale across the entire territory of Ukraine. Our findings indicate that compared to 2021, the planting area and production for winter-triticeae crops decreased during the 2022 conflict, while the planting area and production for rapeseed increased. Crop yield changes were influenced by the intensity of the war, as indicated by changes in nighttime lights. Nevertheless, the influences of the CRF on crop production and food security need to be investigated comprehensively if the war will persist. The study provides new insights into roles of several complex factors in crop production variations. The automated analysis of high-revisit multispectral satellite data enables large-scale, efficient prediction of spatial dynamic information on crop production. This helps governments direct aid to the farmers who need it most. Overall, we provide a comprehensive framework for quantifying crop production dynamics during the war. This framework is scalable, automated, and reliable, with wide potential practical applications beyond the Russia-Ukraine conflict. The developed framework is a valuable tool to evaluate crop production variations, serving as a food-security-early-warning system.

Data availability

MCD12Q1 data is available at https://developers.google.com/earth-engine/datasets/catalog/MODIS_006_MCD12Q1.

MOD09A1 is available at https://developers.google.com/earth-engine/datasets/catalog/MODIS_061_MOD09A1.

MOD11A2 data is available at https://developers.google.com/earth-engine/datasets/catalog/MODIS_061_MOD11A2.

Nighttime light is available at https://developers.google.com/earth-engine/datasets/catalog/NOAA_VIIRS_DNB_MONTHLY_V1_VCMSLCFG#description.

ACLED is available at https://acleddata.com/.

ERA5-Land is available at https://developers.google.com/earth-engine/datasets/catalog/ECMWF_ERA5_LAND_MONTHLY.

HWSD is available at https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/harmonized-world-soil-database-v12/en/.

Agricultural statistics are available at https://ukrstat.gov.ua/.

GADM is available at https://gadm.org/.

Declaration of competing interests

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.

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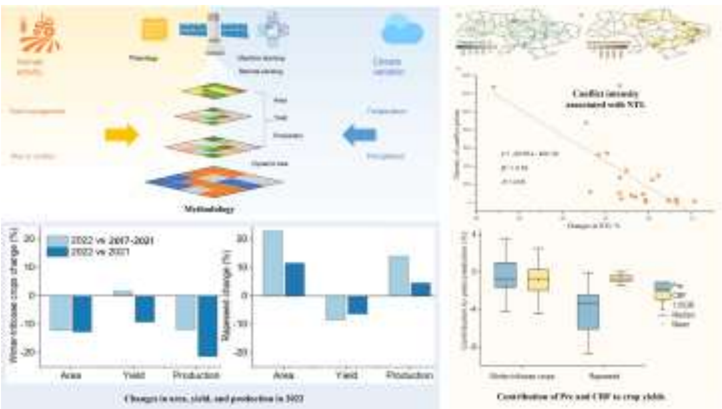
Graphical Abstract



Declaration of Competing Interests

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.