



Impact of the Russian invasion on wheat biomass in Ukraine

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Abstract

Ukraine was the seventh-biggest worldwide producer of wheat in 2021 before the Russian invasion. The war caused a disruption of the global wheat market but the impact on the different levels of the production chain remains unclear. Here we leverage high resolution satellite imagery and crop modeling to analyze specifically the impact of the war on the evolution of the dry aboveground biomass in wheat fields. We compare the Kherson region, a battlefield occupied by the Russian army in 2022 with the Poltava region which was not invaded. We also compare the wheat biomass in both regions in 2022 with the two previous years before the war. We find that the wheat biomass sharply declined in the Kherson region in 2022 only. We interpret this result as a consequence of the abandonment of invaded land by farmers. The lack of agricultural management, in particular the lack of fertilization and irrigation could explain the reduced crop growth in summer, thereby contributing to shortages in the wheat production chain.

1. Introduction

In February 2022, Russia launched a full-scale invasion of Ukraine, marking a significant escalation in the Russo–Ukrainian War that started in 2014. By June 2022, Russian forces had occupied approximately 20% of Ukrainian territory (Clark *et al* 2022). Before the conflict, both nations' exports accounted for 55% of the global sunflower oil market, 35% of wheat, and 19% of maize (Dyson *et al* 2023 after the Food and Agriculture Organization) and Ukrainian Black Sea ports were exporting 6 million tonnes of agricultural commodities each month (Dyson *et al* 2023). Previous studies showed that the war caused significant disruption of the food supply chain, contributing to the global food crisis in 2022 (Chepeliev *et al* 2023, Dyson *et al* 2023, Lin *et al* 2023, Devadoss and Ridley 2024). However, the impact of the war on the global food supply is the result of several cascading effects in Ukraine that are difficult to disentangle, including the destruction of transportation infrastructures, the disruption of fertilizer production, and the massive displacement of the civilian

population. In particular, little is known about the direct impact of the Russian invasion on crop growth in Ukraine due to the lack of official agricultural statistics from the conflict area. In fact, the wheat was mostly planted by Ukrainian farmers before the invasion and it remains unclear to what extent the war had an impact on the biomass at the end of the crop season. In particular, it has been shown that the war had an impact on the water supply systems possibly causing a disruption of water inputs but there is no equivalent information on the nitrogen inputs (Gleick *et al* 2023).

Remote sensing often remains the go-to tool when there is a need to obtain primary up-to-date information on the state of land and infrastructure in the areas affected by military actions. By classifying remote sensing images, (Ma *et al* 2022) found an increase in cropland abandonment especially evident in the southern Ukraine near Kherson. However, they did not analyze the net effect on the crop biomass. (Lin *et al* 2023) further analyzed the wheat cropping area and the wheat evolution using the normalized difference vegetation index, showing signs of wheat

production reduction in Ukraine during 2021–2022. However, this approach does not allow a quantitative evaluation of wheat production.

Here, we use a recent method based on the assimilation of high resolution remote sensing data into an agronomical model that provides estimates of crop biomass at large scale without ground data. Our objective is to quantify the impact of the war on the wheat biomass evolution in the fields. We focused on wheat because it accounts for approximately half of the crop production in Ukraine. Also, many developing countries in Asia, Middle East and Africa rely heavily on imports of Ukrainian wheat (Kobuta *et al* 2012, Mottaleb *et al* 2022, Devadoss and Ridley 2024). We applied this approach to the Kherson and the Poltava regions in Ukraine over three crop seasons. By comparing the evolution of the wheat biomass in both regions, we provide evidence that the war had a direct impact on wheat production near the combat zone.

2. Data and methods

2.1. Study region and period

We focused on two Ukrainian wheat production regions (figure 1), the Kherson and Poltava regions. While the Poltava region was the target of airborne missile attacks, the Russian army did not occupy it, nor was it a place of active combat. In contrast, the Kherson region's border was breached on the first days of the war, and its capital and nearby territories were under occupation from the 1st of March 2022 until the 11th of November 2022, making the region an active battlefield. For convenience in terms of data processing, the area of interest was defined as the extent of the two Sentinel-2 tiles that cover the selected areas (tile 36UVA for the Poltava region and tile 36TWT for the Kherson region). Each tile covers an area of 110 km by 110 km. The 36TWT tile also intersects the Zaporizhzhya region which has also been occupied since the first day of the invasion, and, as of writing this, has yet to be liberated. To determine more accurately the geographical extent of the Russian invasion of Ukrainian territory, we obtained a polygon of the occupied land in 2022 from the State Agrarian Register of Ukraine's Ministry of Agriculture website (<https://minagro.gov.ua/>). We refined this polygon for the period March to May 2022 based on maps and reports publicly available from the Institute for the Study of War website (www.understandingwar.org/). We crosschecked the maps with similar ones published in other sources like Le Monde newspaper and Wikipedia. We performed our analysis for three wheat crop years from 2020 to 2022 (here a wheat crop year is defined as the period from 01 January to 30 October). Cropping years 2020 and 2021 correspond to pre-war conditions while

2022 corresponds to the year of the full-scale Russian invasion.

2.2. Sentinel-2 data level-2A processing

This study relies on Sentinel-2 land surface reflectance products and cloud mask (level-2A) computed using the multi-temporal cloud screening and atmospheric correction software MAJA (figure 2). MAJA is a processor jointly developed by CESBIO and CNES (Hagolle *et al* 2010, 2015) that is unique in its ability to account for the temporal evolution of top-of-atmosphere reflectance to detect the presence of clouds, as well as small changes in surface reflectance due to varying atmospheric aerosol loading. By using a highly conservative cloud mask, precise estimation of aerosol optical depth, and correction for topography and adjacency, MAJA allowed us to obtain a time series of top of canopy surface reflectances from Sentinel-2 with an overall uncertainty of less than 0.01 (Colin *et al* 2023). To further improve the surface reflectance estimates, we utilized auxiliary data from the Copernicus Atmospheric Composition Service (Inness *et al* 2019) within MAJA to account for the actual partitioning of aerosol species. Altogether, we generated 470 products for the 36UVA tile, and 466 for the 36TWT tile.

2.3. Land cover classification

We computed crop maps for the target perimeter using a pixel-level time series classification model to identify the crops, followed by a semantic classification model to mask the non-agricultural areas (urban areas, water surfaces, etc).

First, we used the temporal convolutional neural network to perform the land cover classification (Pelletier *et al* 2019). The model was fed by pixel-level time series of Sentinel-2 L2A products from March to November of every year between 2020 and 2022, considering the 10 spectral bands at 10 m and 20 m. The preprocessing of the time series includes normalization of the reflectance values, resampling of the 20 m bands to 10 m, masking of the clouds and shadows with the built-in masks, daily interpolation, and resampling with a 3 d step. The model predicts a crop class following the nomenclature of 22 classes, including wheat, maize, barley, rapeseed and sunflower classes. The model was trained with 17 million pixel time series, spatially distributed over Austria, Belgium, France, Italy, Netherlands, Portugal, Slovenia and Spain between 2018 and 2021. The pixel labels were extracted from the Integrated Administration and Control System Land-parcel Identification System (LPIS) from several countries. The model reached an overall accuracy of 86% and an F1-Score on the wheat class of 89% on an independent validation dataset covering the same regions and years (approximately 500 000 validation samples by year). This model was applied

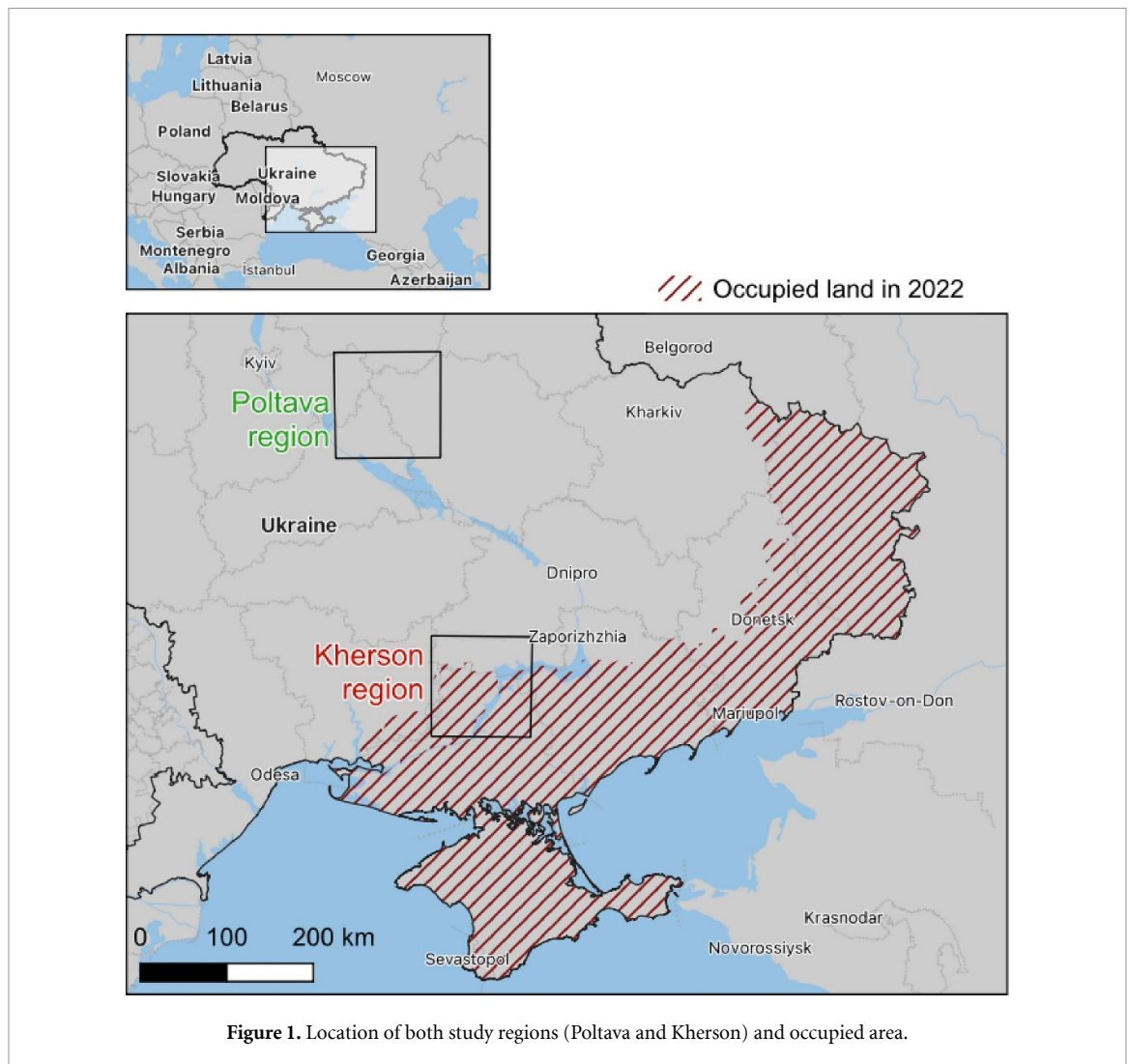


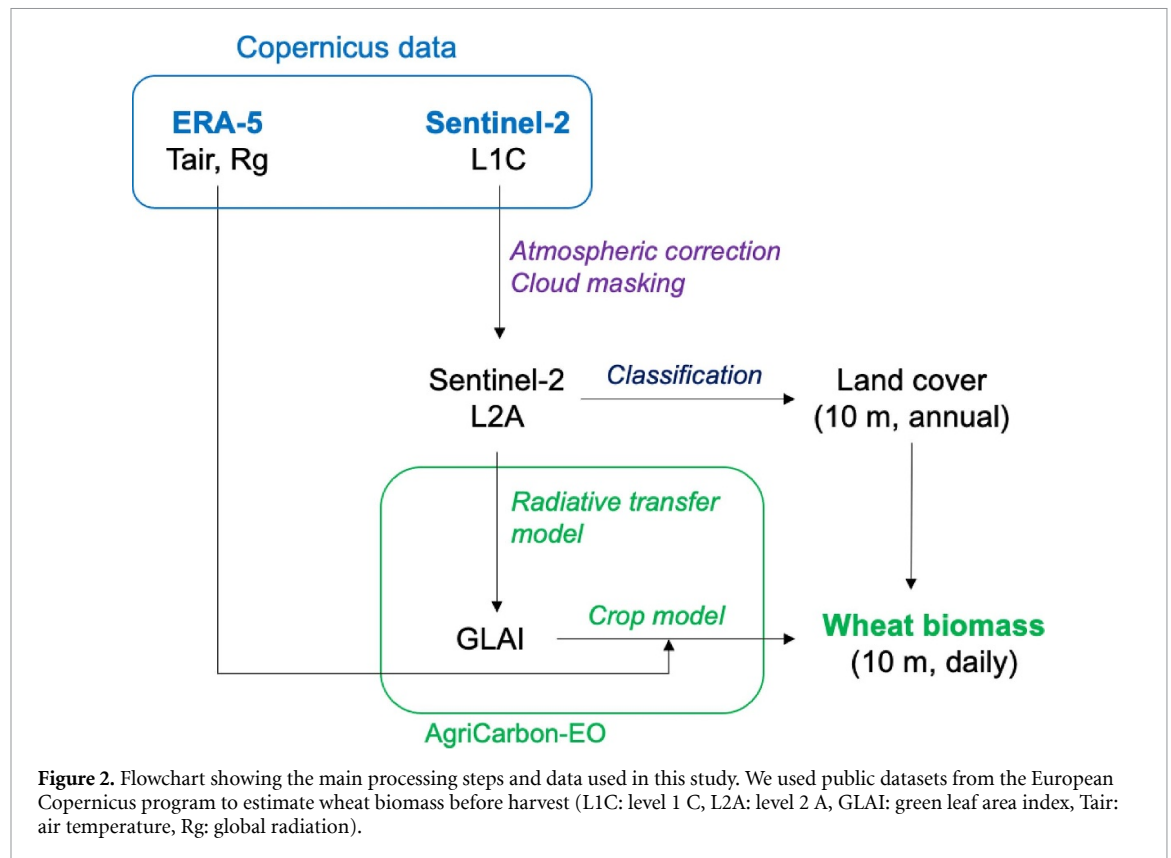
Figure 1. Location of both study regions (Poltava and Kherson) and occupied area.

to the two tiles in Ukraine, yielding a crop classification map for every year. The training over multiple European regions and years ensures the robustness of the model when it is transferred to other regions, as in this study.

Second, the semantic classification was done using a U-Net model, with an encoder based on a pre-trained VGG16 (Simonyan and Zisserman 2015). It takes as input the monthly syntheses of Sentinel-2 surface reflectance products (Hagolle *et al* 2018) of May or June of the target year, working on 256×256 pixels patches and considering the four spectral bands at 10 m (Blue, Green, Red, NIR). This is a binary classification problem, where the model predicts a class (agricultural or non-agricultural) for each pixel of the considered 256×256 patch. The model was calibrated with deep learning techniques on a training dataset of 11 000 256×256 patches distributed all over France in May and June 2020. Data augmentation was used to multiply the number of patches (rotations). The considered ground-truth was the footprint of the French LPIS (RPG)

2020 enhanced with a remote sensing-based classification map (Inglada *et al* 2015). On a distinct validation dataset of 800 patches distributed over France for June 2020, the model reached a global accuracy of 89.9%. After the application of this model on the target tiles and years, we were able to finalize the crop maps by masking the non-agricultural areas. We merged wheat and barley classes to a single 'wheat' class given the possible confusion between both crops.

We compared the aggregated output of this high resolution land cover classification to the official statistics at the region (Oblast) level provided by the Ukrainian administration (www.ukrstat.gov.ua/). The comparison of our classification with the official statistics at the oblast level shows a good agreement on average over the study period between both datasets for all crop cover and years (figure S1). The inter-annual trend differs but we are not fully confident in the reliability of official statistics in 2022 when the war started. However, we note that the uncertainty associated to the wheat area remains unknown in this study due to a lack of a proper validation dataset.



2.4. Wheat biomass with AgriCarbon-EO

We computed the dry aboveground biomass of wheat fields using the AgriCarbon-EO processing chain (Wijmer *et al* 2024). AgriCarbon-EO is an end-to-end processing chain that provides agronomical variables such as phenological stages, biomass, yield, evapotranspiration and CO₂ fluxes (gross primary production (GPP), plant and soil respiration) at daily timestep.

AgriCarbon-EO takes as inputs surface reflectances and associated cloud mask (level 2A products, see section 2.2) annual land cover maps (see section 2.3), meteorological data and crop parameterization. The required meteorological inputs are the daily global incoming solar radiation, the daily average air temperature at 2 m, the daily potential evapotranspiration and the daily cumulative rainfall. Here we used the meteorological data from ERA5-Land (Muñoz-Sabater *et al* 2021).

First, AgriCarbon-EO estimates the green leaf area index (GLAI) and associated uncertainties from the 10 spectral bands of Sentinel-2 using a Bayesian inversion of the PROSAIL radiative transfer model (Baret *et al* 1992, Jacquemoud *et al* 2009). Then, AgriCarbon-EO assimilates the GLAI times series in the SAFYE-CO2 crop model to estimate the agronomical variables. SAFYE-CO2 is a parsimonious agronomical model that runs at a daily time step. SAFYE-CO2 computes the GPP, i.e. photosynthesis, based on an adaptation of the light use efficiency theory (Pique

et al 2020). The daily net primary production (NPP) is then deduced by subtracting the plant daily autotrophic respiration from the GPP (Amthor 2000). NPP is converted into biomass which is allocated to the different organs using allometric coefficients depending on the thermal age of the crop (Baret *et al* 1992). The grain yield can be estimated from the total biomass production at the end of the vegetative period using a harvest index. The assimilation procedure consists of calibrating the prior distributions of 8 parameters in SAFYE-CO2 (see table 1) based on the observed GLAI. The parameters are related to phenology, biomass partitioning and light use efficiency. The remaining SAFYE-CO2 parameters are fixed based on the literature. The assimilation of GLAI to adjust the SAFYE-CO2 crop model parameters is essential to constrain the crop growth to remain as close as possible to the reality. Assimilating GLAI enables to implicitly account for the effect of pest, diseases and various stresses (e.g. nutrients, water availability) on crop development. In order to accommodate SAFYE-CO2 to Ukraine's agro-climatic conditions, we adjusted the prior ranges of SAFYE-CO2 model parameters related to the emergence day (emerg) and the sum of temperature at the start of senescence (Sen_a) (table 1).

The default prior of 'emerg' in SAFYE-CO2 is defined so that the winter wheat growth begins in November–December as generally observed in France (Wijmer *et al* 2024). In Ukraine, the wheat

Table 1. Prior distributions of SAFYE-CO2 crop model parameters.

Name	Description	Unit	Prior [μ , σ , min, max]
Emerg	Day of year (DOY) of vegetation emergence	DOY	[74,20,34 124]
Harv	Day of year (DOY) of vegetation harvest	DOY	[200,0,160,200]
LUEa	Light use efficiency	gCMJ^{-1}	[1.05,0.05,0.8,1.5]
SLA	Specific leaf area	$\text{m}^2 \text{g}^{-1}$	[0.01,0.002,0.004,0.05]
PRT_La	Initial fraction of biomass that is not allocated to the leaves	g g^{-1}	[0.325,0.15,0.01,0.5]
PRT_Lb	Decrease rate of the fraction of biomass allocated to the leaves.	$\text{g g}^{-1} \text{ } ^\circ\text{C}^{-1}$	[1.01,0.005,1,1.02]
Sen _a	Sum of temperature at start of senescence	$^\circ\text{C}$	[1000 200 600,1800]
Sen _b	Rate of senescence	$^\circ\text{C m}^2 \text{m}^{-2}$	[12 000,3000,0,20 000]

goes through a long vernalization period (dormancy) due to snow cover and low temperatures in winter and regrowth occurs in March. Wheat plants before dormancy are hardly detectable from satellite and the model is mostly unconstrained in winter due to the lack of GLAI observations when snow is present. Reliable GLAI observations become available when wheat resumes vegetative growth in March. Therefore, for this study, we shifted the prior distribution of the ‘emerg’ parameter to a normal distribution centered on 15 March (standard deviation of 20 d, minimum date on 3 February, maximum date on 4 May). This prior avoids that the model runs in open loop for a long period. The Sen_a parameter range, which represents the number of growing degree days at which senescence starts was also adjusted from the default value to take into account the Ukrainian climate and the associated wheat varieties.

The outputs of AgriCarbon-EO (e.g. dry aboveground biomass) are produced at the native resolution of Sentinel-2 (10 m) in the Sentinel-2 projection system. For cartographic purposes, we aggregated the variable of interest by ‘hromada’ (‘territorial community’), an official administrative unit in Ukraine (median area of 41 km², median population of 1284).

3. Results

We find a marked decrease of the dry aboveground biomass of wheat fields in the Kherson region in 2022 in comparison with the two previous years (figure 3). In this region, the median dry aboveground biomass dropped from 9.7 t/ha in 2020 and 2021 to 7.8 t/ha in 2022 (20% decrease). In contrast, the dry aboveground biomass did not change significantly in 2022 in the Poltava region with a median value of 10.3 t/ha in 2022 against 10.2 and 10.3 t/ha in 2020 and 2021 respectively (figure 3). Additionally, the spatial distribution of the biomass remained stable in the Poltava region during the 3 year study period, whereas the spatial variability increased in the Kherson region in 2022, with an interquartile range of 1.3 t/ha against 1.0 and 0.9 t/ha in 2020 and 2021 (figure 4). The dry aboveground biomass was below 7 t/ha in some areas (figure 3). By integrating the computed aboveground biomass over the entire wheat area, we obtain

a total wheat aboveground biomass of 3.1 Mt in 2020, 3.8 Mt in 2021 and 2.6 Mt in 2022 in the Kherson study region. These aboveground biomass can be used to estimate yield through the harvest index method (ratio of grain to total biomass). Based on various sources, we estimate that the wheat harvest index in Ukraine ranges from 0.41–0.50 (Tkachuk and Ovcharuk 2020, Novokhatskyi *et al* 2024). Using this range of harvest index values, we can estimate the yield loss in 2022 as the difference of the yield in 2022 with the average yield in 2020 and 2021. Therefore, over the Kherson study region (110 km by 110 km), the wheat grain yield loss in 2022 should range between 0.35 Mt and 0.43 Mt.

From ERA5-Land reanalyze we do not find a specific climatic forcing that can explain the discrepancy in wheat growth between Kherson and Poltava regions in 2022 (figure S2). Air temperature, precipitation and potential evapotranspiration in spring and summer 2022 have intermediate values compared to 2020 and 2021 and do not depart from the climatology.

4. Discussion

The model output indicates that the aboveground biomass in the wheat fields sharply declined near Kherson during the year of the Russian invasion, and there is no evidence of severe climatic conditions that can explain this behavior. Furthermore, the aboveground biomass in the Poltava region remained stable. Therefore, our results show a drop in biomass production in the wheat fields near the front line due to the Russian invasion. Therefore, our results suggest that the Russian invasion caused a drop in biomass in the wheat fields located near the front line. In the studied region this drop is approximately of 20% (in t/ha). There are several hypotheses which can explain this finding. First, we note that the invasion started in February 2022 after the sowing period therefore the impact of the war must be related to other agricultural activities conducted later during the growing season such as irrigation and fertilization. This is corroborated by the fact that the wheat area during the 2022 season was similar to the previous years (2020, 2021) in the Kherson region (figure

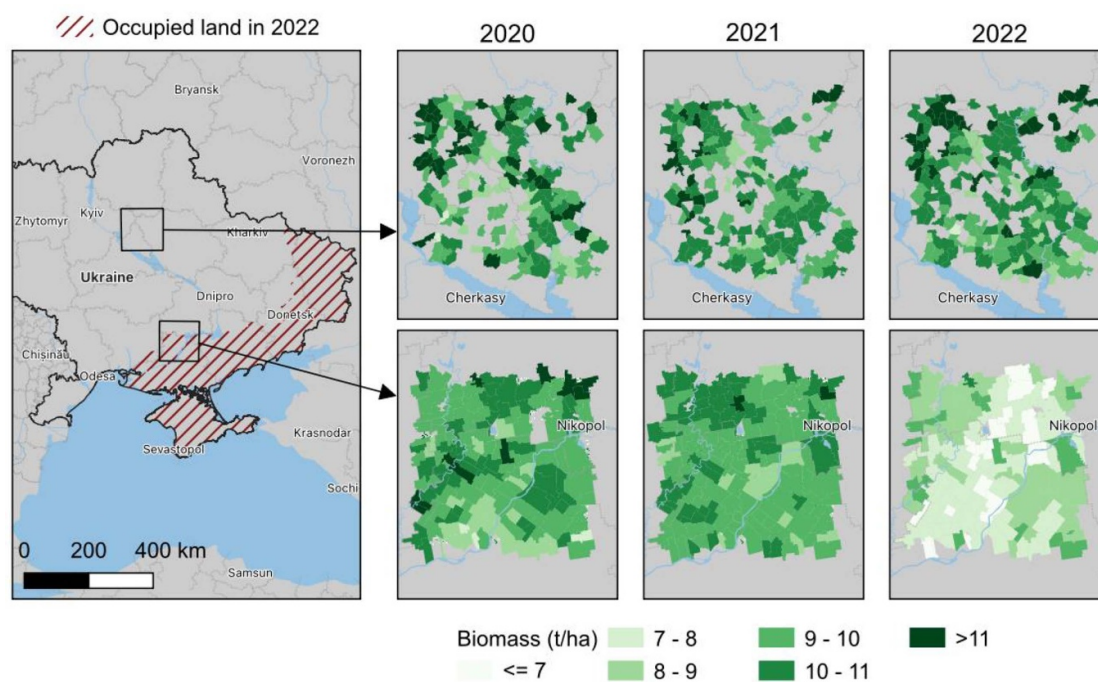


Figure 3. Computed dry aboveground biomass of wheat fields from 2020 to 2022 in both study regions (Poltava and Kherson). The cropping year is designated by the calendar year in which the crop is harvested. The dry aboveground biomass is shown by hromada (official administrative unit in Ukraine), excluding those where the wheat area was below 0.1%.

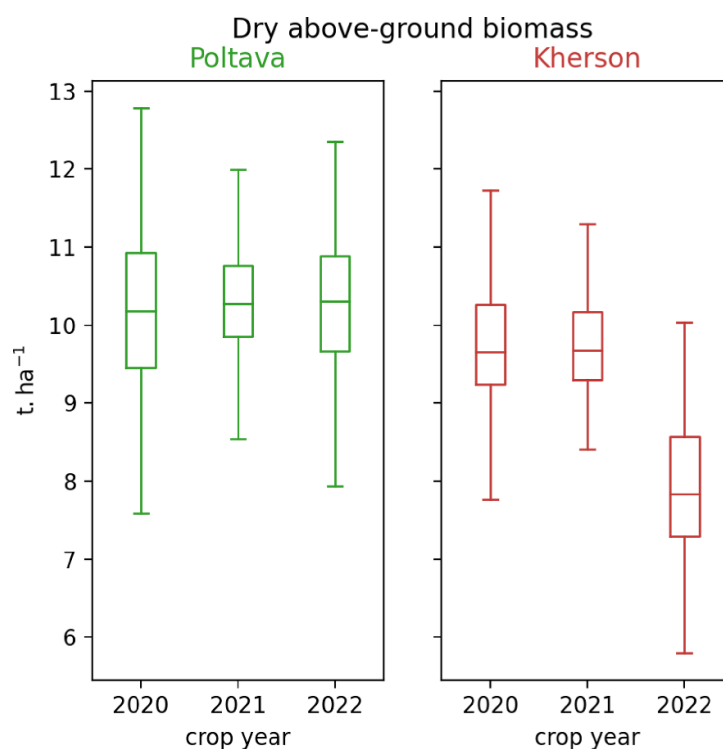


Figure 4. Boxplots of the simulated dry above ground biomass of wheat fields over both study regions and for each crop year.

S1). It is known that the invasion resulted in numerous Ukrainian civilian and military casualties, with estimates suggesting tens of thousands were affected in 2022. The United Nations High Commissioner for Refugees reported that there were over 7 million

Ukrainian refugees across Europe in September 2022 and that the conflict had also led to the internal displacement of nearly 7 million people within Ukraine (UNHCR 2022). In total, one-third of the Ukrainian population had been displaced in half a year. Near

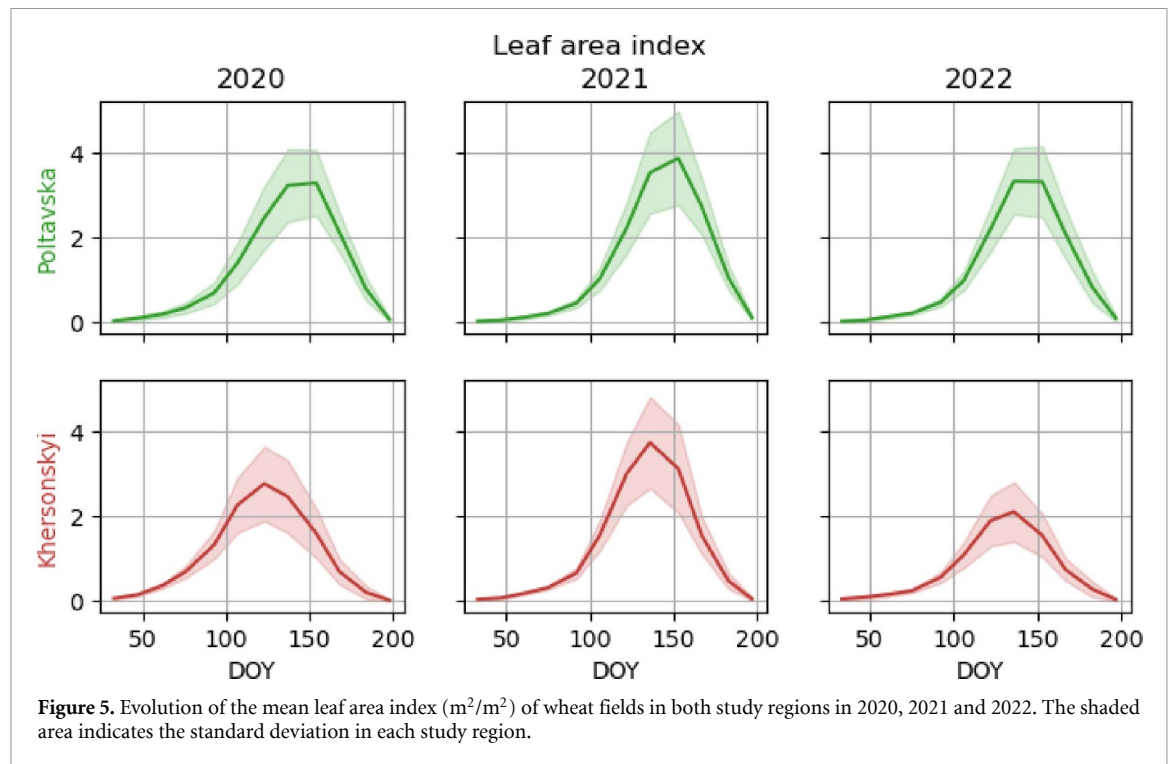


Figure 5. Evolution of the mean leaf area index (m^2/m^2) of wheat fields in both study regions in 2020, 2021 and 2022. The shaded area indicates the standard deviation in each study region.

Kherson, it is likely that many farmers abandoned their fields due to warfare and its consequences—land mines pollution, military fortifications, soil contamination, and the destruction of infrastructure (Neyter *et al* 2022). In conclusion, the war had direct impacts on agricultural production from casualties or displaced population, but impacts on agricultural practices also need to be considered. The lack of agricultural labor during the 2022 wheat crop season has probably caused a strong reduction of water and nitrogen inputs in the Kherson region. Depending on the weather conditions, wheat irrigation is occasionally used in this region of Ukraine. According to the State Statistics Committee of Ukraine (www.ukrstat.gov.ua/), based on the data collected from producers, in 2021 the total harvested wheat area was 503 700 ha, from which 45 400 ha were under irrigation. As most of the Kherson region was under occupation in 2022 the statistical data is not complete after 2021 with official information being given only for enterprises. The total harvested area of wheat in the Kherson region in 2022 was 33 400 ha from which only 3300 ha were declared as irrigated. To disentangle the role of nitrogen (fertilization) and water (irrigation) from the low total biomass estimates near Kherson, we analyzed the evolution of the leaf area index as estimated by Agricarbon-EO throughout the three crop seasons (figure 5). The data indicate that the wheat growth was already reduced before summer at day-of-year 100 (i.e. 10 April). A lack of irrigation would impact the late-season growth of winter wheat crops in Ukraine (Pysarenko *et al* 2021). Given

that winter precipitation was close to normal in the Kherson region (figure S2), root zone soil moisture was probably not yet depleted at that time of the year. Precipitation was rather low between May and July 2022, which may have caused a soil moisture deficit in summer (figure S2), but it is quite late in the season. For a reduced proportion of fields that had a late growth season, we cannot exclude that irrigation stoppages also contributed to reducing wheat growth later in summer. Hence, the most plausible explanation for reduced productivity over the majority of the fields is the lack of nitrogen inputs. This is due to the impossibility of applying fertilizers in the region of conflict, and the disruption of the fertilizer supply, in particular, due to the occupation of the main port terminals in South Ukraine (Shahini *et al* 2022). This can be corroborated by a survey carried out by the Ukrainian government, which estimated that 40% of the required Nitrogen fertilizer was available during 2022 (FAO 2022).

Our conclusions are strongly constrained by remote sensing observations. They are also in line with previous reports of hotspots of fallowed and abandoned croplands near Kherson (Ma *et al* 2022). Our estimates of yield loss in Kherson region are in agreement with other estimates at the oblast level (Deininger *et al* 2023, Panek-Chwastyk *et al* 2024). We used multi-temporal and multispectral optical data, which are not subject to radio-frequency interferences due to spoofing and on-ground military radars, unlike passive or active microwave remote sensing data (Sørensen *et al* 2023). The main limitation,

inherent to conflict regions, is the lack of *in situ* data to evaluate or recalibrate the models. It was not possible to evaluate precisely the quality of the land cover maps over the areas of study. The only available comparison with the oblast scale official data suggests that our estimates are reasonable (figure S1). Furthermore, the crop assimilation system and AgriCarbon-EO parameters are calibrated for winter wheat across Europe but not specifically over Ukraine. This may introduce systematic error in biomass estimates, but should not affect the relative variations between years and regions that form the basis of our conclusions.

5. Conclusion

In this study, we estimate that the Russian invasion of Ukraine affected wheat production upstream of the food supply chain by reducing crop growth. Our results show a reduction of 20% in wheat aboveground biomass over the Kherson region near the front. To accomplish this, we applied a methodology based on the exploitation of optical remote sensing into machine learning algorithms for the production of the land cover maps, and assimilation into physically based crop modeling for the production of agro-variables, mainly aboveground biomass. Our agro-variables analysis across two regions in Ukraine and three years shows that the reduction is not associated with climatic conditions but rather because of the inability to implement agronomical practices during the growth season, especially nitrogen fertilization. This effect should therefore be considered in addition to other processes related to the quality of crops, the failure of logistics of exports, and international trade to fully understand the 2022 global disruption of the wheat supply chain.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: <https://doi.org/10.5281/zenodo.12749818>.

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Conflict of interest

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

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