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

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ABSTRACT

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

1. Introduction

The war that started with Russia's attack on Ukraine on February 24, 2022 has already taken a vast human and economic toll, triggering migration of at least 6.3 million people having left to neighboring countries and, based on UNHCR estimates, 6.6 million who are internally displaced and 13 million people stranded in affected areas or unable to leave.[1] Implications for regional and global food security will be far-reaching, with 41.5 million ha of highly fertile land larger than the agricultural area of France (18 million ha), Germany (12 million ha) and Poland (11 million ha) combined, given Ukraine's traditional role as a breadbasket and a main exporter of wheat and sunflower oil. After the start of the war, grain prices rose well above the levels experienced in the 2007/08 food crisis, highlighting agriculture's geostrategic role (von Cramon-Taubadel 2022).

As the blockade of its Black Sea ports and the lack of alternative routes with comparable capacity challenges Ukraine's ability to exporting agricultural produce, countries such as Egypt, Indonesia, and Lebanon that are highly dependent on Ukrainian food imports already experienced shortages. The dearth of storage space for the 2022 season resulting from the inability to export sufficient volume, together with war-induced shortages of key inputs such as fuel, fertilizer, seed, or labor, may affect farmers' planting and crop management decisions in the 2022 season and beyond. This could depress not only local welfare but would also imply that, instead of realizing its potential for intensification of wheat production (Swinnen et al. 2017), production losses in Ukraine will exacerbate global food insecurity.

For decision-makers to minimize the negative impact of this disruption in the short term and prevent dis-investment and the associated erosion of productive capacity in the longer term, granular in-season data on agricultural production can be of great utility. This paper show how remotely sensed information can be used to quantify damage from conflict at field and village level; link these to area cultivated with winter crops (wheat, barley, rye, and rapeseed)[2] and use the

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[1] See https://www.unrefugees.org/emergencies/ukraine/.

[2] On average for 2019–2022, rapeseed accounts for approximately 13% of winter crop area and 87% of winter cereal area is covered by wheat with the rest devoted to barley and rye.

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Normalized Difference Vegetation Index (NDVI) of winter cereal fields as a proxy for expected yield of these crops to estimate direct conflict impact on crop area and expected yield and identify villages particularly affected by the shock. While doing so allows to estimate the impact of direct crop damage on output, we also obtain a year-specific residual that, to the extent that included covariates control for non-war related time varying effects, could be interpreted as the macro-economic effect of the war on winter crops area cultivated or expected yield of winter cereals.

Having such information in real time at high levels of granularity can provide information to allocate scarce resources for crisis response to areas with demonstrated needs. Examples include directing emergency support to farmers who suffered losses; ensuring availability of equipment for harvesting; planning logistics and providing avenues for short-term grain storage (plastic tubes) in areas where predicted harvests exceed available storage capacity either due to war damage (Khoshnood et al. 2022) or because storage could not be emptied; and ensuring availability of inputs and working capital for the next season especially to those who may have lost their harvest due to war. While we use the example of Ukraine, the type of analysis we perform is of much broader applicability.

To generate such information, we use a 4-year (2019–22) panel of 10,125 village councils (VCs) for which reliable crop cover information based on a machine learning model using ground-truthed training data is available. To quantify war-related disturbances relevant for agriculture, we identify location and extent of damages to agricultural fields via burning, explosion of ordnance, rockets, or aircraft, and soil compaction from movement of tanks or heavy artillery based on manual change detection using repeat high-resolution imagery (see samples in the Appendix).

We then apply panel econometric methods to provide estimates of war effects on the extent of area grown with winter crops and, for winter cereals fields, peak NDVI as a predictor of crop yield, both at VC level. Panel regressions that include data on precipitation and accumulated temperature are used to control for time varying effects. Village fixed effects are included to control for time invariant effects such as soil quality, infrastructure access, or social cohesion and effectiveness of local leadership. For the years without conflict, these covariates together explain more than 92 % of the variation in the data for cultivated area, allaying concerns about omitted time-varying factors confounding winter cereal area estimates. To establish a relationship between NDVI and winter cereal yield, we use Ukrainian data to translate NDVI into an estimate of expected yield.

Estimates suggest that direct effects of the conflict on area cultivated with winter crops are relatively modest (a reduction of about 0.14 million ha compared to 9.35 million ha in a situation without conflict) but there is a large year-specific negative residual (of 0.83 million ha). If this residual was entirely attributable to the conflict, war-induced effects would be associated with a reduction of area grown with winter crops by slightly more than 10 %, most due to macro-factors rather than direct field damage. Adding changes in wheat yield implies a total reduction of output of 4.84 million tons that is close to estimates produced by the EU but significantly below those by USDA, possibly because the latter excludes output produced in areas that have been occupied by Russia since February 2022. Expected winter wheat yields drop most in rayons (administrative units equivalent to counties in the US) with a larger share of small producers, suggesting that conflict hurts small farmers most given their more limited access to diversification options.

Our findings relate to and contribute to three strands of literature. First, while a large body of studies discusses the link between conflict and food security, the case most frequently encountered in developing country contexts is one where shocks to food production—or the value of agricultural endowments more generally—trigger conflict. We show that a case like Ukraine where causality runs from conflict to food production, can be analyzed using satellite imagery to generate measures of agricultural production as outcome variables as well as indicators of conflict beyond what is routinely discussed in the literature and, for the latter, demonstrate that our measure outperforms measures of conflict used routinely in other studies.

Second, most of the literature focused on direct impacts of conflict events, including on long-term outcomes such as human capital. The massive population movements, economic disruption, and input shortages experienced by Ukrainian farmers due to the war suggest that, in addition to direct effects, indirect ones may be important. Constructing a panel of VCs allows to obtain a time specific residual that captures all time-specific changes not explicitly controlled for in the regression. While further research and a more structural approach to identify impact channels will be desirable to assess the extent to which the 2022 output drop can be interpreted as a conflict effect, we are confident that the data generated here will provide a valuable basis for doing so.

Finally, in disaster or conflict situations, gathering reliable data to inform decision-making is often a challenge and many analyses involve significant time lags. Our study shows that remotely sensed data provide a timely, granular, and reliable option to inform design of measures (e.g., cash or in-kind transfers or opening up of markets) for immediate crisis response to improve resilience and prevent longer-term erosion of productive capacity and assess their impact. Timeliness, though, comes with some limitations. Methodologically, there is some need for use of simplifying assumptions (e.g., to use winter cereals instead of wheat and to rely on threshold segmentation rather than training data as field data collection was impossible). Although it will be difficult to do so at this point, the justification for such shortcuts can be tested as more data become available, providing a basis for fruitful interaction with policy-makers and providers of agricultural statistics to help devise new ways of planning and providing market information. Substantively, while the field level evidence provided here will reflect producers' expectations of the market situation, we provide estimates of expected harvest volume that may be above what reaches the market due to factors such as intentional crop burning by enemy armies,[3] lack of resources to harvest or facilities to store grain, and disruptions in logistics and supply chains. Quantification of these issues, as well as extension of the analysis presented here to summer crops, is left to future research.

The rest of the paper is structured as follows. Section two provides background and motivation and introduces the strategy to estimate direct and indirect impacts of conflict. Section three describes data sources and highlights descriptive evidence. Section four presents econometric results for winter crop cover and NDVI of cereals and discusses their implications. Section five concludes by highlighting potential policy relevance and areas for future research.

2. Motivation and approach

2.1. *Conflict and food security in the literature*

Weather or price shocks that affect households' relative endowments are often viewed as potential triggers for violent conflict (see McGuirk and Burke (2020), Berman et al. (2021), or Blair et al. (2021) for a discussion and references). Studies of the impact of violence on food security focus almost exclusively on the consumption side; in fact, the review by Martin-Shields and Stojetz (2019) includes no studies that directly analyze conflict impacts on food production. Thus, while such studies highlight the need for proper counterfactuals and use of panel data, Ukraine's situation is sufficiently different from that analyzed in most studies on conflict and food security limiting the transferability of

[3] See https://forbes.ua/inside/cherez-rosiyski-obstrili-lishe-za-lipen-zgorilo-70–000-ga-zernovikh-shcho-tse-oznachae-dlya-ukraini-17082022–7744 for an estimate of such activity for July 2022.

substantive insights and requiring a different analytical approach.[4]

Remotely sensed imagery covers large areas consistently and can thus be used to monitor agricultural outcomes. Satellite imagery is routinely deployed to consistently quantify global changes in land use such as deforestation (Hansen et al. 2013) or map crop type at continental scale (d'Andrimont et al. 2021). In the US, a Landsat-based crop data layer is available since the 1980 s to allow parcel-level analysis (Lark et al. 2017). For developing countries, the use of imagery to provide reliable output or productivity indicators down to the plot level has recently been demonstrated (Lobell et al. 2020) with access to ground-based training data being a key constraint (Burke et al. 2020). Easier access to imagery and cloud computing platform to store data and provide computing power has greatly increased extent, scope, and granularity with which satellite imagery is used to assess damages due to conflict since the review of studies on this topic by Witmer (2015).

Documenting conflict effects in urban areas requires very high resolution imagery as illustrated by Mueller et al. (2021) who develop a machine learning algorithm applied to Syria.[5] Effects of war on agricultural production can rely on lower resolution imagery as illustrated by studies such as Alix-Garcia et al. (2013) for Darfur and a number of studies covering areas of the former Soviet Union including Ukraine to assess determinants of land use—including land abandonment (Meyfroidt et al. 2016), grazing intensity (Dara et al. 2020), and crop cultivation (Munteanu et al. 2017)—over rather long time periods (Matasov et al. 2019).

We build on insights from recent studies using satellite imagery by using interpretation of readily available imagery from the European Union's Copernicus Sentinel 2 constellation to construct an indicator of whether or to what extent a VC is directly affected by the war. Imagery also allows us to construct the two main outcome variables considered in our analysis, i.e., the area grown with winter crops and, for fields growing winter cereals, the NDVI as a measure of yield, for the 2019–2022 period at VC level. At the same time, we follow the literature on conflict impacts in terms of using a robust econometric framework to estimate conflict impacts as discussed below.

2.2. Estimation strategy

To estimate conflict effects at a high level of spatial disaggregation and in a way that allows appreciation of possible heterogeneity, we construct a panel data set covering 10,125 village councils (VCs) over the period 2019–2022. This allows the use of a difference-in-differences approach to estimate conflict impacts on a wide range of variables. Indexing village councils by v and year by t, the model to be estimated is

$$Y_{vt} = \alpha_v + \beta CI_{vt} + \gamma X_{vt} + \lambda_t + \varepsilon_{vt} \tag{1}$$

where Y_{vt} is the outcome variable of interest in village v at year t; CI_{vt} is a vector of conflict variables including an indicator for presence (or intensity) of different types of conflict at village level that takes a value of zero for years prior to 2022 and for villages that did not suffer direct conflict-related damages in 2022, and area of fields damaged by war-related actions based on either satellite imagery or public sources as discussed in more detail below; X_{vt} is a vector of time varying weather variables that includes number of growing degree days (GDDs) and precipitation[6]; α_v are village fixed effects that control for time invariant factors such as agronomic suitability, access to infrastructure and economic opportunities, and local leadership quality; λ_t are time fixed effects; and ε_{vt} is random error term.

Two sets of coefficients in (1) are of particular interest: a vector of estimated coefficients β measures the direct impact of conflict-related activities and damaged crop area in affected villages while λ_{2022} captures the deviation of 2022 from the common mean. To the extent that time invariant variables such as access to infrastructure, soil quality, or village leadership and time variant climatic variables are controlled for, this can provide an upper bound estimate of indirect conflict effects and interacting the 2022 dummy with relevant characteristics would allow to explore heterogeneity of conflict effects among different types of producers or VCs.

To illustrate how this approach can be applied, we estimate this regression for two outcome variables. The first, area grown with winter crops by May 1, allows us to cover the extensive margin. As winter crop planting decisions had been made before the conflict started, we expect the size of such effects to be relatively modest. The second, predicted yield (proxied by NDVI) on area planted with winter cereals, relates to the intensive margin, in particular the ability to manage crops properly considering shortages of cash, labor, or inputs. For fields that, based on our crop classification are planted with winter cereals,[7] we use the NDVI, computed on the GEE platform, as a proxy for crop conditions and expected yield. Agronomic studies including Dhillon et al. (2020) for the US, Vannoppen and Gobin (2021) for Western Europe, and Nagy et al. (2021) for Eastern Europe show that, for winter wheat, the NDVI, ideally combined with weather data (Aula et al. 2021), provides rather accurate yield prediction. An early application for forecasting winter wheat yields in the US and Ukraine was by Becker-Reshef et al. (2010). We use village level data for the period 2019–2020 to estimate the marginal effect of increases in NDVI on winter wheat yield under recent Ukrainian conditions and use it for prediction.[8]

2.3. Ukraine's context and motivation

With 41.5 million ha of highly fertile land, Ukraine has traditionally been a major source of food grains. Before the war, agriculture contributed about 10 % to GDP and 42 % of the county's exports. After de-collectivization in the early 2000 s, when some 7 million landowners were provided with land shares of about 4 ha each, the agricultural sector's value added doubled. Some 20 million ha of Ukraine's agricultural land is farmed by large farms, often by firms with links to foreign capital markets (Deininger et al. 2018); 12 million ha is cultivated by small and household farms; and some 9.2 million ha was originally under state or communal land, a sector the size of which has been reduced significantly by disposing of public land, often in non-transparent ways.

The war has disrupted implementation of far-reaching structural reforms relating to agricultural land in Ukraine. To increase investment, diversification and climate resilience by making property rights more secure,[9] strengthen decentralization and transparency by allowing local

[4] As exposure to violence often leads the poorest to revert to subsistence as in Colombia (Arias et al. 2019), levels of food consumption may not decline linearly with conflict exposure as shown in Afghanistan (D'Souza & Jolliffe 2013). This has led to use of dietary diversity as a more appropriate measure of conflict impact there (D'Souza & Jolliffe 2014), in Nigeria (George et al. 2020), and Cote d'Ivoire (Dabalen & Paul 2014).

[5] Wouters et al. (2021) similarly use UAV imagery in Malawi to assess flood-related damage to houses.

[6] We include levels and quadratic terms to allow for decreasing marginal effects from rain or temperature or negative flooding or drought effects.

[7] As wheat accounts for about 87% of winter cereals, we use winter wheat and winter cereals interchangeably.

[8] Noting that the NDVI for winter wheat attains its maximum shortly before anthesis, most studies use the peak NDVI (Johnson et al. 2021) or the value of this variable just prior to anthesis even if Panek and Gozdowski (2020) obtain the best fit with NDVI values from a slightly earlier date.

[9] Several factors, including the lack of a unified lease registry, a mix of digital and paper documents, corruptible registrars, courts and police forces, and legislation prohibiting registration of leases shorter than 7 years that tends to drive landowners into informality, further reduce users' ability to enforce leases, diverting resources from investment or reducing incentives for it.

Table 1
Village council level conflict indicator (two-week periods since the start of the conflict).

	Crop area damage		Occupied	Active	Troops	Any
	Yes	if yes, area		Fighting	present	indicator
P1: Feb 24 - Mar 12	0.009	268	0.04	0.08	0.120	0.122
P2: Mar 13–26	0.023	450	0.097	0.059	0.156	0.163
P3: Mar 27 - Apr 10	0.006	161	0.08	0.019	0.099	0.103
P4: Apr 11 – 24	0.011	458	0.081	0.018	0.099	0.102
P5: Apr 25 - May 7	0.008	254	0.080	0.018	0.098	0.100
P6: May 8–22	0.009	184	0.080	0.018	0.098	0.101
P7: May 23 - Jun 3	0.014	286	0.080	0.018	0.098	0.103
P8: Jun 4–18	0.011	272	0.080	0.018	0.098	0.101
Total P1 - P8	0.048	614	0.123	0.106	0.179	0.187

Note: The sample comprises 10,125 Village Councils (VCs) that were under Ukrainian control in 2015 (i.e., excluding Crimea and areas occupied in 2014) that have a positive area cultivated with winter crops in 2019–2022.
Source: Own computation from satellite images (columns 1–2) and open source data https://novy.tv/ru/news/2022/06/02/karta-bojovyh-dij-v-ukrayini/ and https://liveuamap.com/ru/time (columns 3–5).

governments to generate tax and lease revenue from public land for local service provision, and foster mortgage lending, the government had adopted a package of laws that included the lifting of a moratorium on agricultural land sales that had been in place since the early 2000 s and that depressed investment and productivity in the sector (Nivyievskyi et al. 2021).[10] A mandatory shift to transparent electronic auctions of state land doubled lease prices received by local governments (Deininger et al. 2022). Between July 1, 2021 when the moratorium was lifted and the start of the war that led to temporary suspension of land markets,[11] some 0.25 million ha of agricultural land was transferred by sale or purchase.

Table 2
Extent of training samples and F1 scores for winter crops.

Year	Total	Extent of training sample			F1
	sample size	Winter cereal	Winter rapeseed	Summer crops	
2019	2,481	508	271	1702	99.3
2020	3,155	543	263	2349	97.0
2021	3,644	699	292	2653	99.9
2022*	2,132	354	116	1662	95.1

Note The F1 score is TP/(TP + 0.5*(FP + FN)).

Beyond the broader human and economic toll from the war, agricultural production in 2022 and possibly beyond will be affected by three factors. First, as an estimated 20 million tons of maize and wheat from the 2021 crop were still in storage when the war started, the

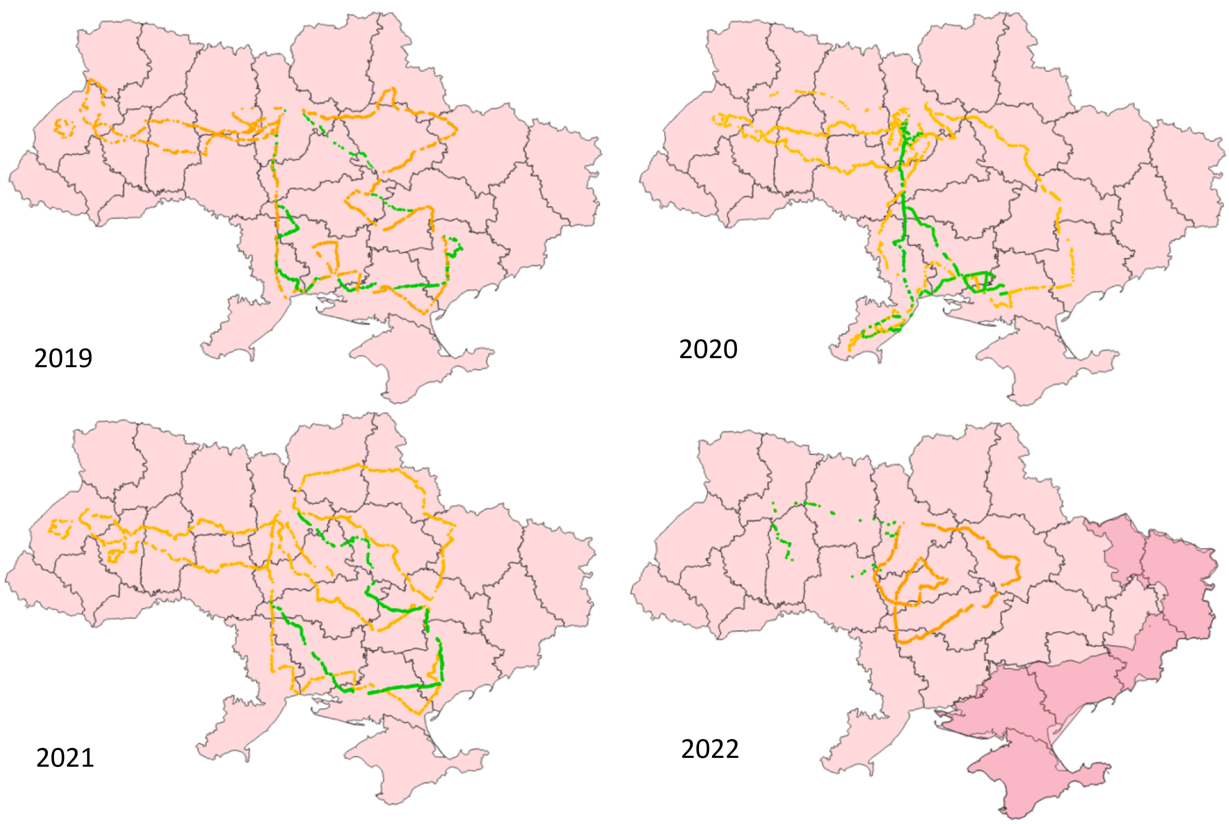

Fig. 1. Routes for in-situ training data collection, 2019–2022. *Note:* Green and orange refer to the paths of ground data collection for winter and summer crops, respectively. Area in a darker shade of red is currently occupied by Russian forces. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

[10] Similarly, Zadorozhna (2020) finds evidence of corruption in land markets, Graubner et al. (2021) suggest presence of market power, and Kvartiuk et al. (2022) discusses lack of transparency in land auctions used to lease out state land.

[11] Three laws to govern land relations under martial law (laws 2247-IX; 2254-IX, and 2255-IX) were passed on May 12.

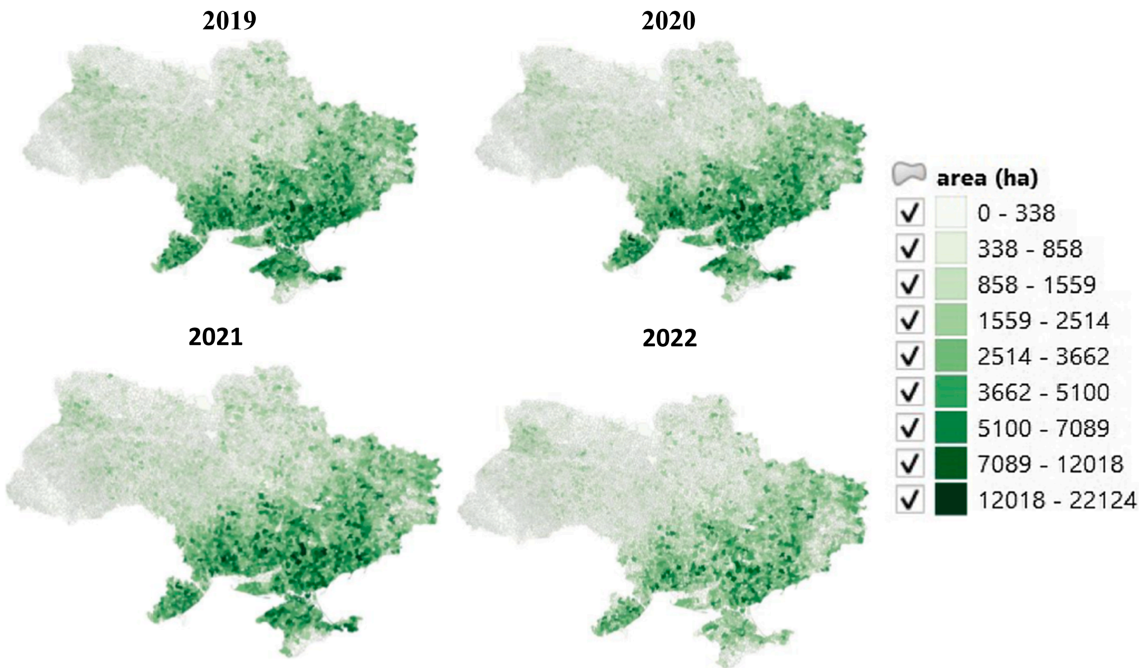

Fig. 2. Map of winter crop cover for 2019 to 2022 growing seasons.

Table 3
Area planted with winter crops and NDVI of winter cereals, national and by VC and conflict status.

		2019	2020	2021	2019–21	2022	Diff 2022 vs 2019–21 absolute	Diff 2022 vs 2019–21 %	No. VCs
Panel A: National winter crop area (million ha)									
Winter crop area		9.430	7.514	9.461	8.801	8.383	−1.047	−11.10	10,125
Panel B: VC level winter crop area (ha)									
Total		931.4	742.1	934.4	869.3	828.0	−103.40	−11.10	10,125
Crop damage	No	890.3	704.5	892.0	828.9	795.1	−95.24	−10.70	9,748
from imagery	Yes	1,992.4	1,713.8	2,031.0	1,912.4	1,678.1	−314.29	−15.77	377
Occupied	No	818.4	645.3	803.7	755.8	721.0	−97.40	−11.90	8,894
public source	Yes	1,747.7	1,441.6	1,879.0	1,689.4	1,600.9	−146.75	−8.40	1,231
Active conflict	No	870.4	687.2	867.5	808.4	771.1	−99.32	−11.41	9,071
public source	Yes	1,455.9	1,214.8	1,510.0	1,393.6	1,317.4	−138.51	−9.51	1,054
Russian troops	No	792.4	616.3	772.6	727.1	699.9	−92.48	−11.67	8,330
public source	Yes	1,576.1	1,325.7	1,685.2	1,529.0	1,422.0	−154.04	−9.77	1,795
Panel C: VC level NDVI of winter cereals									
$NDVI_{ww}$ May 11		0.731	0.660	0.703	0.698	0.694	−0.037	−5.06	9,302
$NDVI_{ww}$ May 21		0.738	0.682	0.705	0.709	0.720	−0.019	−2.51	9,302
$NDVI_{ww}$ May 31		0.794	0.654	0.790	0.746	0.722	−0.072	−9.10	9,302
$NDVI_{ww}$ June 11		0.781	0.712	0.765	0.753	0.738	−0.043	−5.53	9,302
NDVI Max		0.836	0.765	0.838	0.813	0.775	−0.061	−7.29	9,302
Crop damage	No	0.836	0.766	0.840	0.814	0.776	−0.060	−7.18	8,826
	Yes	0.819	0.748	0.806	0.791	0.743	−0.076	−9.31	476

Note: As explained in the text, $NDVI_{ww}$ is the NDVI for all fields categorized as winter cereals in the crop cover analysis for the year in question. The difference between columns 4 and 5 indicates the deviation of 2022 outcomes from those observed in 2019–2021.
Source: Own computation from crop maps for winter crop area and sentinel imagery 2019–22.

blockade of traditional export routes though Ukraine's Black Sea ports reduces export revenue and—combined with a lack of fuel and transport capacity—threatens to give rise to depressed producer and elevated consumer prices. Limited capacity of alternative channels for grain export via Poland or Romania and targeted destruction of some grain silos exacerbate this constraint.

Second, destruction of land and crops through war-related actions (bombs, land mines, or movement of heavy vehicles) directly reduces the productive potential of a given piece of agricultural land. Finally, shortages of fuel, inputs such as seed, fertilizer, and pesticides, or labor make it difficult, particularly for small farmers, to properly manage winter crops or plant summer crops and will likely be associated with reduced output. Taken together, these have been estimated to have a large impact: Aggregate assessments put total direct damages in agriculture at US$ 4.29 billion (Neyter et al. 2022b)[12] and estimate indirect war-induced losses in

[12] Of this total, about 50% is for land (mining pollution) and unharvested winter crops, 21% for machinery, 14% for stored products, 6% for storage facilities and the remainder for livestock, perennial crops and inputs.

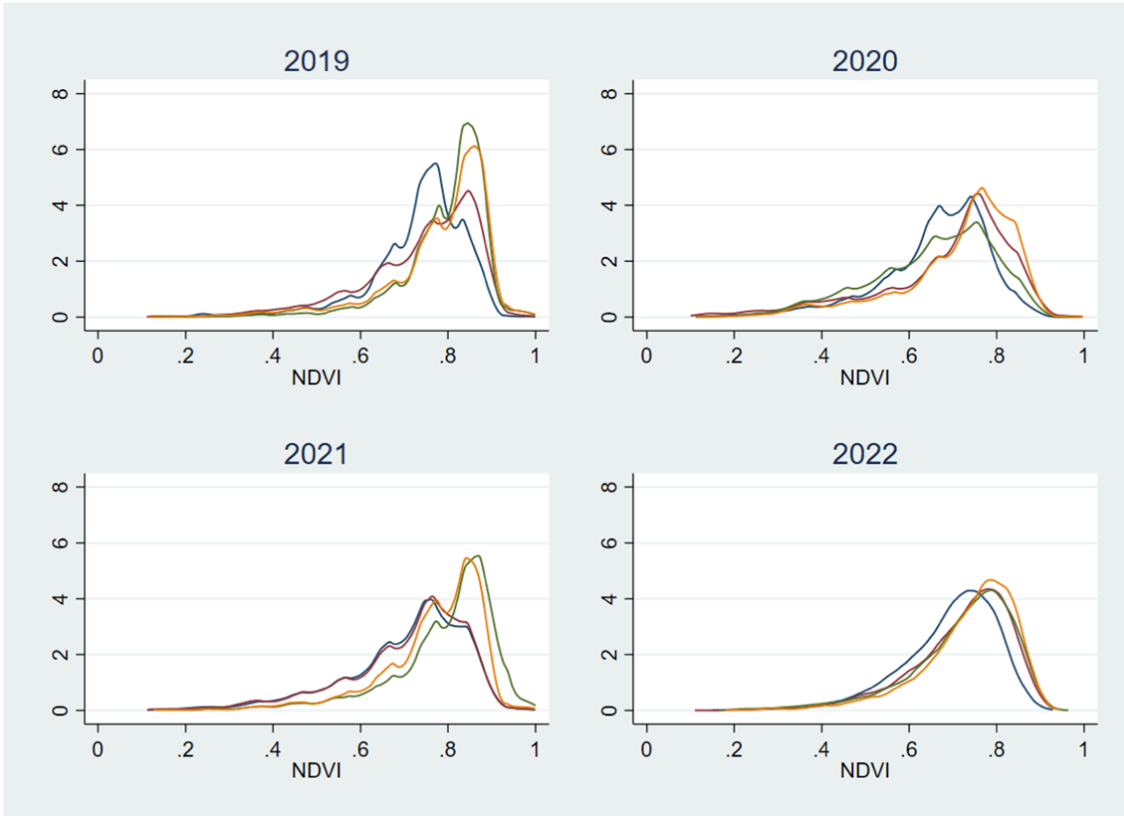

Fig. 3a. Density of NDVI for fields grown with winter cereals for different time periods, 2019–22. *Note:* Blue = May 1–11; Red = May12- 21; Green = May 22–31 Orange = June 1–11. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

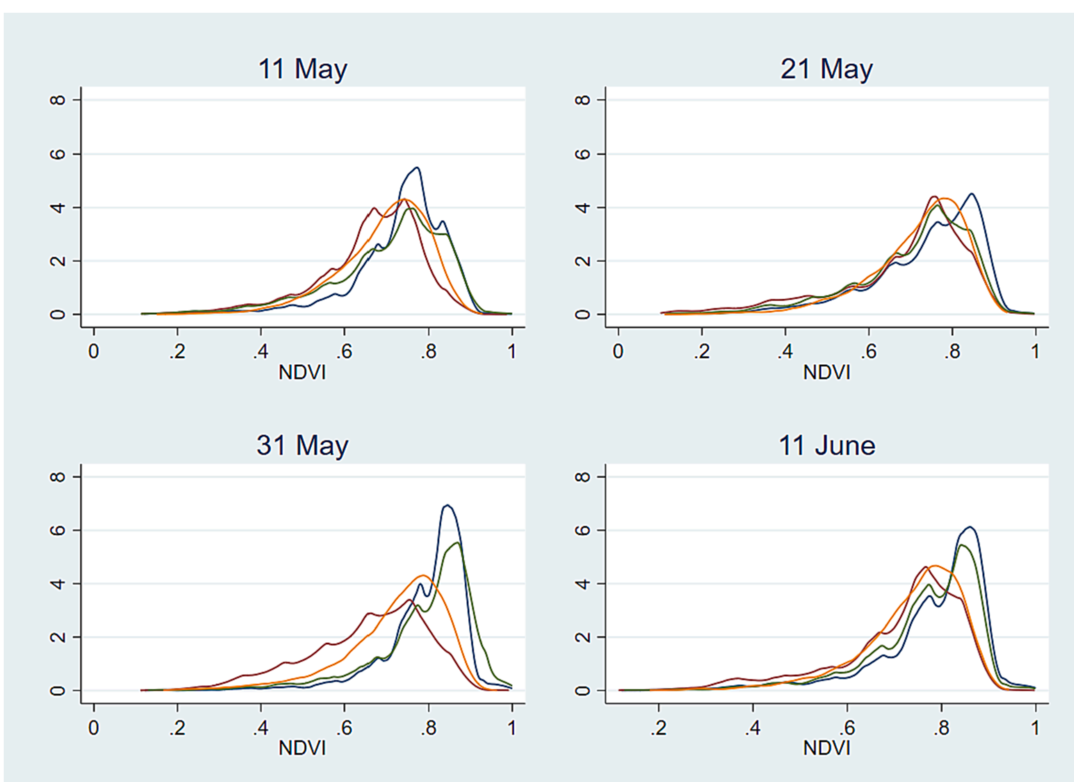

Fig. 3b. NDVI for fields grown with winter cereals at different dates during the growing season, 2019–22. Note: Blue = 2019; Red = 2020; Green = 2021; Orange = 2022. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

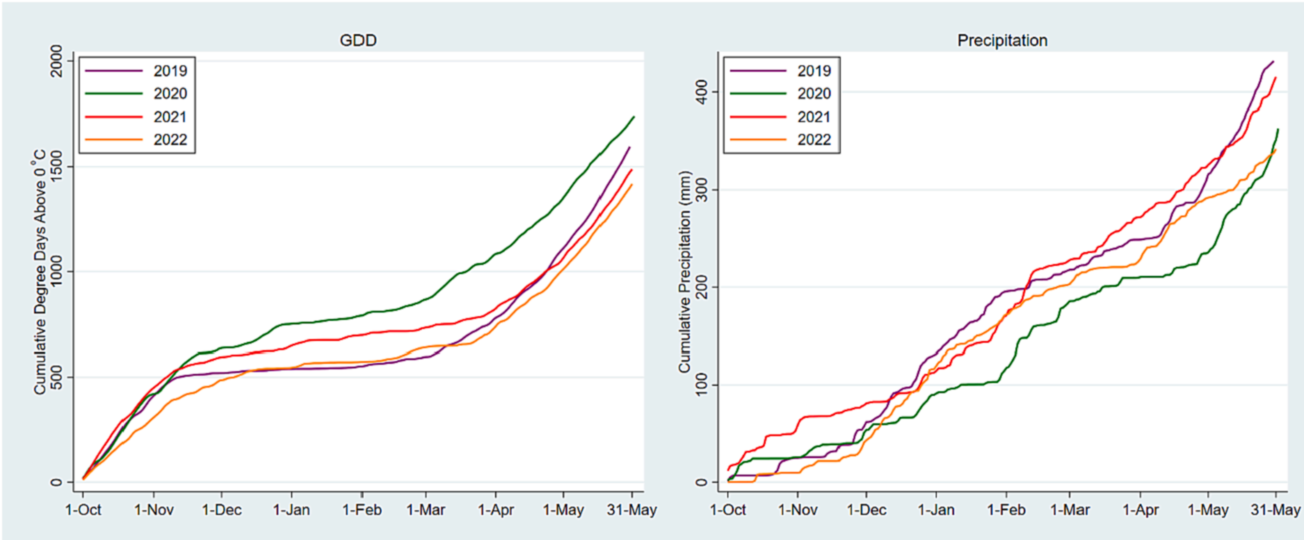

Fig. 4. Cumulative mean growing degree days (GDD) above 0 °C and daily rainfall October 1 – May 31.

the agricultural sector to amount to US$ 23.3 billion, with logistics disruptions (US$ 11.9 billion) and lower output (US$ 9.6 billion) as main elements (Neyter et al. 2022a).[13] Our approach can provide not only a methodologically sound underpinning for such estimates but also an opportunity to disaggregate them and explore their heterogeneity.

3. Data and descriptive statistics

3.1. Incidence and effects of conflict

We use two measures of villages' direct conflict exposure. First, leveraging the high spatial and temporal resolution of Sentinel-2, we rely on manual comparisons of cloudless Sentinel-2 and Planet satellite imagery with imagery for the same locations in the same month before the war in bi-weekly intervals to identify conflict-related damages to specific fields in the 9 oblasts (districts) directly affected by military action.[14] The basis for our analysis is the geometrically and atmospherically corrected harmonized multi-spectral Sentinel 2 surface reflectance product available in GEE which allows for consistent analysis over time. Although a machine learning model to distinguish three types of damages, i.e., burning, explosion craters, and soil compaction due to movement of heavy vehicles, is under development, the data used here is based on manual analysis performed by local students.

One advantage is that they quantify the extent of damages using a metric, i.e., area of fields damaged by fighting, likely to be more relevant for agricultural outcomes than standard indicators for the severity of conflict such as the number of casualties as reported by Armed Conflict Location and Event Data (ACLED) as described by Raleigh et al. (2010).

To informally check our method's external validity, we compare the location of damaged fields based on our interpretation of satellite images to the location of military action during the relevant two-week period as reported by the ACLED as the standard source of information used in conflict research (Raleigh et al. 2010). Appendix Table A1 shows that, except in the early phases of the war, 98 % of damaged fields are located within 20 km from settlements with active fighting as reported by ACLED. This suggests that direct field damage is likely to occur only in close geographical proximity to areas with active military action. On the other hand, military activity will not always result in field damage, e.g., if it is concentrated in urban areas. Panel A of Appendix Fig. A1 displays, for one of the sub-periods analyzed, locations with military activities and damaged fields, supporting this conclusion graphically. Panel B of Appendix Fig. A1 where white lines denote settlement boundaries shows that interpretation of imagery provides a more precise measure of the location and magnitude of field damages than standard conflict data coded up to the nearest settlement. Of course, the image-based measure could in principle be disaggregated along other dimensions.

To illustrate the underlying principle, Appendix Fig. A2 includes figures with examples of 'before-after' images showing the most frequent types of damages such as fields having been hit by bombs, rockets, aircraft wreckage, or artillery shells; having been the scene of direct fighting and associated fires; or crops having been destroyed or damaged due to traffic by heavy vehicles and tanks. For each VC and any of the two-week periods after February 24, 2022, we define an indicator variable for whether such damage was sustained and, if yes, add up the size of agricultural area affected.

Summary statistics for these variables are presented in the first two columns of Table 1 for two sub-periods. Values of the first 8-week period from February 24 to April 24 are used in regressions for winter crops area and values of the second 8-week period from April 25 to June 18 (together with values from February 24) are included as right-hand side variables in NDVI regressions. By April 24, 3.7 % or 379 VCs nation-wide had been affected by direct damages to fields with an average damaged area of 498 ha per VC. This had increased by one point to 4.8 % by June 18 with an average damaged area of 614 ha. By June 18, the total area of damaged fields stood at 292,262 ha (476*614).

Intertemporally, the largest extent of damages occurred in period 2 when damages were experienced in 2.3 % of villages, decreasing to 0.6 % in period 3 and 1.1 % in period 4, largely in line with the abandonment of positions in areas surrounding Kyiv and Kharkiv by the Russian army. The share of VCs experiencing crop area damage then dipped below 1 % in periods 5 and 6, while surpassing it (with 1.4 % and 1.1 %) in periods 7 and 8. In affected villages, the intensity of fighting was about equal in periods 2 and 4, damaging about 450 ha per affected VC before subsiding and then increasing again in periods 7 and 8.

In addition to image-based data on direct damages, information on

[13] Output is assumed to fall by 33% for wheat, 32% for sunflower, and 31% for barley; 18% for maize; and 22% for other crops (fruits and berries).

[14] These oblasts are Kyivska, Chernigivska, Sumska, Kharkivska, Luganska, Donetska, Zaporizka, Khersonska, and Mykolaivska. A machine learning model to automate this process is under development.

Table 4
Results from fixed-effects regression for winter crop area.

	Conflict indicator					
	None	Under occupation	Conflict actions	Troop presence	Any	Conflict intensity
Conflict indicator		−27.249*	2.074	−48.046***	−51.485***	−94.916***
		(15.705)	(17.026)	(14.009)	(13.933)	(18.708)
Area with crop damage (ha)	−0.137***	−0.135***	−0.138***	−0.116***	−0.111***	−0.100***
	(0.030)	(0.030)	(0.031)	(0.030)	(0.031)	(0.031)
Year 2020	87.085***	77.504***	87.546***	67.161***	65.310**	56.513**
	(24.779)	(25.386)	(25.067)	(25.447)	(25.465)	(25.491)
Year 2021	46.265**	44.750**	46.360**	41.301**	40.628**	42.893**
	(20.473)	(20.491)	(20.488)	(20.520)	(20.525)	(20.475)
Year 2022	−101.168***	−95.792***	−101.477***	−89.024***	−87.918***	−82.129***
	(13.864)	(14.206)	(14.094)	(14.307)	(14.318)	(14.358)
No. of obs	40,500	40,500	40,500	40,500	40,500	40,500
R-squared	0.095	0.095	0.095	0.095	0.095	0.096

Note: Results are from 2019 to 2022 panel regressions where the unit of observation is the village council and the dependent variable is the area covered with winter crops as of May 1 of the relevant year. Crimea and areas that have been occupied since 2014 are excluded. 'Any' (column. 5) is the maximum over the 4 two-week periods considered whereas 'conflict intensity' (col 6) accounts for the temporal dimension by taking a value of 1 for any of the 4 two-week periods when any conflict activity was observed. See Appendix Table A5 for full specification including weather variables. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table 5
Predicted direct and indirect effects of conflict on winter crop area in ha.

	Total	Village councils with conflict activity?				Occupied by Russia
		No	Yes			
			Total	Field damage?		
				No	Yes	
(1) Full model (B)	8,383,053	5,728,333	2,654,720	1,996,448	658,273	1,785,863
(2) No conflict (S1)	8,519,392	5,728,333	2,791,059	2,090,035	701,025	1,858,003
(3) No macro & conflict (S2)	9,350,952	6,406,968	2,943,984	2,211,997	731,987	1,924,446
(4) No macro conf., weather (S3)	9,429,938	6,452,591	2,977,347	2,236,432	740,916	1,951,350
(5) Net conflict effect (S1-B)	136,339	–	136,339	93,587	42,752	72,140
(6) Net macro effect (S2-S1)	831,560	678,635	152,925	121,962	30,962	66,443
(7) Conflict & macro effect (S2-B)	967,899	678,635	289,264	215,549	73,714	138,583
(8) 2019 weather (S3-S2)	78,986	45,623	33,363	24,435	8,929	26,904
No. of VCs	10,125	8,263	1,862	1,485	377	809

Source: Own computation based on coefficients from Table 4 column 6.

whether VCs were occupied, a scene of active conflict, or counted with Russian troop presence is available online based on daily situational reports from local and regional military administrations at the level of settlements.[15] We draw on these sources to compute indicators of relevant parameters including a dummy for any conflict activity. Columns 3–6 of Table 1 show that by phase 4, 18.4 % of VCs had been affected by any conflict activity. As subsequently the conflict entered a more static phase with active fighting concentrated in the East of the country, information on the location of fighting or troop presence shows less change over time and information on field damages provide a more informative signal.

3.2. Winter crop cover

To provide training data for generation of crop cover estimates using machine learning techniques, *in-situ* data collection along main roads (Waldner et al. 2019) following JECAM guidelines[16] was undertaken yearly from 2019 to 2021. In each year, two extended field trips, one for the winter and one for summer crops, were conducted (see Fig. 1 for route maps in each year). Cloud-free satellite imagery from the period during which ground data were collected was then used to hand-label contiguous blocks of clearly identifiable crop cover that were used to train the machine learning model.

While conflict conditions prevented *in situ* data collection during the spring, a ground survey for the 2022 crop was eventually organized in June 2022. Crop maps for 2019–21 build on analysis performed by Kussul et al. (2017); Shelestov et al. (2017), and Shelestov et al. (2020) who used optical data from Sentinel-2 and SAR data from Sentinel-1 during the vegetation period using a convolutional neural network on the Amazon Web Services cloud computing platform as well as a random forests classifier on the Google Earth Engine (GEE) platform.[17] A winter crop mask for 2022 was created by computing the maximum NDVI for all of Ukraine in any two-week interval between February 1 to May 31 on GEE and applying threshold segmentation.[18]

Table 2 shows the number of training samples for winter and summer crops collected each year as well as the F1 scores for winter cereal

[15] Open source conflict monitoring data (https://novy.tv/ru/news/2022/06/02/karta-bojovyh-dij-v-ukrayini/ and https://liveuamap.com/ru/time).

[16] https://jecam.org/wp-content/uploads/2018/10/JECAM_Guidelines_for_Field_Data_Collection_v1_0.pdf.

[17] See Kussul *et. al* (2016 and 2017) for a detailed description of methodology for crop mapping based on satellite data. We use the classification map based on a deep learning model on AWS, as it is more accurate at small fields.

[18] Threshold segmentation was based on maximum NDVI values and to separate winter cereals and rapeseed, an additional band index was calculated to detect the characteristic yellow flowering of winter rapeseed (d'Andrimont et al. 2020). While ground truth data collection was still ongoing when the original manuscript was prepared, data are now available and a robustness check using these data rather than those obtained via threshold segmentation is conducted. Appendix Fig. A3 plot area of winter cereals obtained using the above approach against those reported by state statistics at oblast level, suggesting high and significant correlation. The plot of VC-level winter crops area estimated either using threshold segmentation or based on ground truth data in Appendix Fig. A4a shows very high correlation between the two approaches.

classification maps which exceeds 95 % in each of the years (detailed confusion matrices are presented in Appendix Table A2). Maps of the estimated winter cereal area by VC generated on this basis as displayed in Fig. 2 illustrate a concentration of winter cereals in the country's South and East and suggest a much lower level of winter cereal cover in 2022 and to some extent in 2020 than in 2021 and 2019.

Panel A of Table 3 supports this by showing that, with 8.38 million ha, area cultivated with winter crops in 2022 is indeed 11 % below the 2019–21 average but well above the 7.5 million ha attained in 2020 when adverse weather conditions led to widespread winter crop failure, especially in the southern and central part of the country. Figures at national level are in line with those reported in the JRC's MARS bulletin (Ben Aoun et al. 2022) that attributes most of the changes to differences in weather, highlighting the importance of controlling for such factors before attributing changes over time to conflict.[19]

A first step towards assessing direct conflict impacts is to compare the deviation of 2022 winter crop area from the 2019–21 level between VCs that were affected by the different types of conflict and those that were not affected. Results from doing so, reported in panel B of Table 3 point towards three relevant factors. First, in conflict-affected villages, winter crop area is more than double that of non-affected ones, suggesting that conflict disproportionately affected villages with high winter crop potential.

Second, winter crop area in VCs where crops were damaged directly is significantly lower (by 15.7 %) than in VCs that did not experience such direct damage (where the decline was 10.7 %), suggesting that interpreting satellite imagery provides additional information. Third, none of the other open source-based indicators affect changes in winter crop area; in fact, reductions in winter crop area in VCs unaffected by conflict are higher (though not significantly so) than in those affected by conflict. Determining whether the decline in winter crop area is due to conflict-related shortages of labor, fuel, or other inputs needed to carry out the necessary crop management activities or climatic factors will require econometric analysis.

As the literature suggests that for winter wheat satellite-based estimates of NDVI can reliably approximate yield,[20] we use the crop masks obtained from the above land cover analysis for 2019–2022, respectively, to compute NDVI on all fields planted to winter cereals for consecutive two-week periods during the growing season on the Google Earth Engine cloud computing platform.[21] NDVI values were then aggregated at village level. Fig. 3a illustrates NDVI densities for different periods in each year. For all years except 2021, peak NDVI values are attained in the first 10 days of June. To allow a comparison of NDVI across years at different growth stages, Fig. 3b presents levels of NDVI on fields with winter cereals on May 11, May 21, May 31, and June 11 which leads to a similar conclusion. Tabulating VC-level figures in panel C of Table 3 confirms that NDVI in 2022 was uniformly lower than in earlier years.

3.3. Weather conditions and farm structure

To control for time-varying effects that are unrelated to conflict, we use information on precipitation as well as minimum and maximum temperature derived from the United States National Centers for Environmental Prediction Global Forecast System (GFS) that produces weather forecasts every 6 h. For the 2019–2022 growing seasons, we use the first 6-hour interval of each forecast as a "nowcast" to derive daily aggregated values at rayon level using GEE scripts. Temperature data is then converted into growing degree days using the sinusoidal distribution as suggested by d'Agostino and Schlenker (2016).

Data on cumulative GDD days at 0 °C computed based on daily values of T_{min} and T_{max} in Fig. 4 illustrates a marked seasonal pattern and clear differences across years.[22] Most relevant for our analysis are a warm winter and spring in 2020; a mild winter followed by a cool spring that provided favorable growing conditions in 2021; and 2022 starting with a cold fall and remaining the coolest of the four growing seasons thus far, leading to delayed crop development and harvest dates.

Data on precipitation in Fig. 4 highlights that, in addition to having been unseasonably warm, the 2020 season was very dry, with abnormally low winter rainfall followed by a spring with long dry spells that contributed to a cumulative water deficit of 70–100 mm compared to 2019. This resulted in widespread winter crop failure, especially in the South and Center due to insufficient soil moisture, as indicated by reports in Ukrainian-language websites referred to such climate-induced decline in crop area during the 2020 season.[23] While official statistics do not differentiate between winter and summer wheat and summer wheat may have been widely used to replant fields where winter wheat had failed, they point to a 10 % decline of the wheat harvest in 2020 as compared to that in 2019 (27.49 million tons vs 24.74 million tons), compared to 31.16 million tons in 2021. Official statistics also show that this change was regionally differentiated: Compared to 2019, output in 2020 dropped by almost 20 % in the South and 15 % in the Center and North but increased by 11 % in the East and declined only modestly (by 6 %) in the West.[24]

Larger farms, especially if they have foreign connections, may be able to overcome war-related challenges in terms of accessing inputs and liquidity more easily than smaller ones. To test if this is the case with our data, we use 2020 data from the Ukraine State Statistics Service' reporting 'Form 29' to compute, for every rayon, the share of crop area by farm enterprises that cultivate between 500 and 2,500 ha or more than 2,500 ha nationally, i.e., either in the rayon or in other parts of the country.[25] Results in Appendix Table A3 illustrate that 78.5 % of area in the average rayon is cultivated by farms operating more than 500 ha and 45.5 % by ones operating more than 2,500 ha, a share that is slightly higher in rayons that experienced direct crop damage.

4. Results from econometric analysis

4.1. Results and damage estimates from crop cover regression

If the 2022-year dummy is to be interpreted as an indicator of indirect conflict effects, we need to make sure it is not merely picking up unobserved time-varying factors. To check on this, we regress winter crop area and NDVI on weather variables and village dummies using

[19] The importance of adjusting for time-varying factors is illustrated by Schierhorn et al. (2021) who find that weather and climate variables explain 54% of country-level winter wheat yield variability in Ukraine.

[20] Dhillon et al. (2020) report that the best fit is obtained most to the Feekes scale (Large 1954), i.e., between 97 and 112 GDD above 0°C.

[21] Due to a change in Sentinel 2 data processing that was introduced with version 4.0.0. end of January 2022, GEE's S2_SR_HARMONIZED collection was used for 2022 NDVI values.

[22] In line with the empirical pattern, we define fall as the period between October 1 and December 1; winter as the period between December 1 and March 1; and spring as the period thereafter.

[23] https://espreso.tv/news/2020/05/02/na_pivdni_odeschyny_subtropichna_posukha_znyschyla_70_ozymyny; https://suspilne.media/38003-na-pivdni-ukraini-agrarii-vtracaut-vrozaj-zernovih-cerez-posuhu/; https://www.kyivpost.com/business/losses-of-winter-crops-in-ukraine-due-to-drought-reach-2–6.html.

[24] Raw data is extracted from the official website of State Statistics Service of Ukraine: https://www.ukrstat.gov.ua/.

[25] Unfortunately, information from form 29 on farm size distribution is reported only at rayon level. As this implies that identification is based on 32 conflict-affected rayons (see Appendix Table A3), it should not come as a surprise that interacting the farm size indicator with other time invariant effects, as suggested by a reviewer, results in less precise coefficient estimates. Data on the distribution of formally registered and informal farms at village level could help to address this and will be an important area for future research.

pre-war data only. Results, reported in ApAppendix Table A4, show that these variables explain about 92 % of the variation in winter crop area, allaying fears about potential upward bias of the estimated coefficient of the 2022-year dummy due to omission of other variables affecting crop area. Table 4 summarizes results from estimating equation (1) with detailed results in Appendix Table A5.[26] While area of damaged crops based on imagery is included throughout, other indicators of conflict and an index for 'any' exposure are introduced one at a time in columns 2–5 given their collinearity. An index of conflict intensity that accounts for duration is included in column 6, our preferred specification.[27] Three insights are noteworthy.

First, time invariant and time-varying variables are all highly significant; the null hypothesis of all village fixed effects equaling zero is decisively rejected. Direct conflict impacts are highly significant: a VC having been exposed to any type of conflict in all four periods is estimated to reduce cultivated area by some 95 ha, in addition to a highly significant point estimate (of −0.10, see column 6) for crop area directly damaged. An effect below a 1:1 reduction is plausible result as only a fraction of a VC's area will be planted to winter crops and some types of damage (such as movement of heavy vehicles or localized explosions) is unlikely to result in total crop loss even if it reduces yield.

Second, the negative and highly significant time dummy for 2022 points towards a statistically significant time-specific residual that may reflect war-induced manpower shortages, difficulties of accessing purchased inputs, especially fuel, or an expectation of lacking market demand when the crop will be harvested. The estimated area reduction of 82.1 ha per VC (column 6) amounts to about 8.8 % of winter crop area, a large effect given that planting decisions for winter crops had been made before the war so that conflict-related effects would essentially involve abandonment of already planted areas. Comparing estimated coefficients across years illustrates that, after controlling for village fixed effects and weather-related factors, winter crop area in 2021 and 2020 exceeded the 2019 level by 42.89 and 56.51 ha, respectively, implying that a simple comparison of 2022 to earlier years would overstate the impact of conflict by 50 % or more.

Finally, as Appendix Table A5 illustrates, the coefficients on weather-related variables and their squares can be given a plausible interpretation: cumulative GDD above 0 °C and precipitation variables (except rain in the fall) are positive and highly significant, though they exhibit decreasing marginal returns. The positive and statistically significant coefficient on the number of dry days in fall is quantitatively large, i.e., an additional dry day is estimated to increase winter crop area by 58 ha or about 7 % of the village average winter crop area.[28] This is consistent with the notion that, in light of the need to harvest predecessor crops (mostly maize or sunflower), prepare the soil, and sow the winter crops, time for field operations in fall is often a binding constraint on the ability to plant winter crops and that overly wet conditions may force farmers to grow spring crops instead.

To translate regression coefficients into an estimate of direct and possible indirect conflict-related effects at national level, we use the estimated coefficients to predict winter crop area for the baseline and two counterfactual scenarios the first of which assumes that there is no direct conflict effect while the second assumes absence of both direct and indirect conflict effects.[29] Table 5 reports predicted winter crop area overall for the 10,125 VCs of interest (column 1) and, to illustrate the underlying mechanisms, separately for the 8,263 VCs unaffected (column 2) and the 1,862 VCs affected (column 3) by conflict with the latter again subdivided into 1,485 VCs where no direct crop field damages from conflict was sustained and 377 where such damages were incurred. In column 6, we also report results separately for the VCs that were occupied by Russia where winter crops may be grown but output will not contribute to Ukrainian GDP.

Total predicted winter crop area is 8.4 million ha, 5.7 million ha in VCs unaffected by direct conflict and 2.7 million ha in VCs affected by conflict (2 million ha in VCs without and 0.7 million ha in VCs with fields being damaged directly by conflict related activities). As lines 2 and 4 in Table 5 illustrate, scenario one, i.e., hypothetical elimination of direct conflict, will change winter crop area only in VCs directly affected by conflict, with a predicted increase in area of 136,339 ha (93,587 ha in VCs without and 42,752 ha in VCs with direct field damage from conflict). By comparison, eliminating the macro effects of conflict is predicted to increase winter crop area by 831,560 ha, most (678,635 ha) due to changes in VCs that are not directly affected by conflict. In other words, of the total estimated reduction in winter crop area, 14 % is due to direct war-induced damages and up to 86 % can be attributed to macro-effects. With an average yield of 4 tons/ha, this would translate into a loss of winter crop output of close to 4 million tons. An interesting question that could be answered by follow-up analysis is how much of this shortfall would be compensated by having some of the fields in question planted with summer crops.

4.2. *Results and damage estimates from NDVI regression for winter cereals*

Beyond substitution of summer crops for the winter crop area lost as a result of conflict, further losses can be due to conflict-induced yield reductions even for areas remaining under winter crops. As 87 % of winter cereal area (or 76 % of winter crop area) is devoted to wheat, a crop the yield of which has been shown to be closely correlated to NDVI, we use our regression model to explore potential conflict-related yield effects. Table 6 reports summary estimates from estimating equation (1) with (peak) NDVI, rescaled between 0 and 100, on winter cereal fields as dependent variable where the structure in panel A is identical to that of Table 4 and panel B adds farm size interactions.[30] In the preferred specification (column 6) all coefficients of interest are significant at 1 % (panel A) and interactions at 5 % (panel B). With an R^2 of 0.36, independent variables explain large part of within VC variation and the significance of coefficients on weather and year effects highlights the importance of a regression approach to obtain unbiased estimates (Appendix Tables A7 and A8).

While the literature suggests peak NDVI predicts wheat yields with high accuracy, studies come from different geographies and produce a wide range of estimates. For data from the 2012–2016 growing seasons in Poland, the Czech Republic, and Eastern Germany, Panek and Gozdowski (2020) find that an increase of 0.1 in early season (until mid-May) NDVI increased grain yields by between 1.1 and 2.6 tons/ha or by 25 %-50 % with R^2 of between 0.5 and 0.85. For Argentina, Lopresti

[26] Appendix Table A6 presents results based on winter crop area estimated after ground truth data collection for the year 2022 was completed. The results (compared to those reported in Table 4) show that the NDVI threshold segmentation approach used to estimate winter crop area for the year 2022 provides robust estimates.

[27] This index takes values of 0, 0.25, 0.5, 0.75, or 1, depending on the number of periods when 'any' conflict indicator was 0.

[28] Based on the regression, the optimum number of dry days in fall would be 34.3.

[29] In terms of the model results reported in Table 4 col (6), scenario one involves setting the 'any conflict' dummy and 'damaged field area' to zero whereas scenario two involves in addition setting the 2022 dummy to zero.

[30] See Appendix Tables A7 and A8 for a full set of coefficients where the consistent high significance of climate variables suggests that ignoring these would yield biased estimates. Substantively, results imply that GDD and precipitation increase yield at a decreasing rate while zero rain days in fall are estimated to have a convex and zero rain days in spring a concave relationship with winter cereal NDVI and winter rain is insignificant.

et al. (2015) find an increase of yield of 109 kg/ha with each additional point of peak NDVI measured by MODIS data (R^2 of 0.53). For 10 seasons in the 2000–2013 period from South Africa's Free State, Mashaba et al. (2017) find that MODIS-based NDVI values from up to 30 days before anthesis have most predictive power (with an R^2 of 0.73) with a 0.1 point change in the NDVI predicted to increase wheat yield by 1.21 tons/ha (from a mean of about 2.2 tons/ha). To ensure comparability with the literature, the below discussion rescales coefficients from Table 6 to be in line with NDVI measured on scale of 0 to 1.

As we have village-level data on wheat yield for 2019 and 2020, we can estimate this relationship directly for Ukrainian conditions with dependent variables used here. Results from village-level regressions of yield for a third-degree polynomial of NDVI with and without village fixed effects are in Appendix Table A9.[31] Appendix Fig. A5 uses corresponding marginal effects to highlight that the marginal effect peaks at between 0.7 and 0.8 before decreasing modestly. Based on the regression with village fixed effects, we pick a 56 kg/ha change per 0.01 change in NDVI for prediction purposes.

The point estimate (-0.0026 per 100 ha) on area directly damaged by war-related activity together with a mean of about 500 ha of direct damage would imply a yield reduction of 72.8 kg/ha (0.0026*5*56/0.01) or a loss of 40,177 tons.[32] With a coefficient of −0.019 on the conflict indicator, exposure to direct manifestations of conflict throughout the period would imply an additional yield reduction of 106 kg/ha (0.019*56/0.01) of winter cereal in the VC. Noting that conflict-affected VCs cover about 632,606 ha and have on average been exposed to conflict action for four of the eight two-week periods, this implies a direct conflict-induced loss of 29,169 tons of winter cereals (632,606*0.5*0.106*0.87 where 0.87 is the share of cereals in winter crop area). We also find a statistically highly significant 2022-year dummy, with a point estimate of −0.052,[33] implying a yield reduction of 289 kg/ha or 7.2 % average yield. With the 2022 winter crop area at 8.383 million ha (see Table 3), this would imply conflict-induced output losses of 2.11 million tons of winter cereals (8.383*0.289*0.87). Adding the above figures (2.11 + 0.0402 + 0.0292) and multiplying by 0.87 (the share of winter wheat in winter cereals) implies an output loss of 1.9 million tons which, if added to the 2.94 million tons of lost output (total estimated winter crop area loss of 967,899 ha multiplied by 0.76, the share of wheat in winter crop and 4 tons, the average wheat yield) due to area reduction implies a maximum war-induced loss of winter wheat amounting to 4.84 million tons.

To test if farmers with larger operational holdings that are more likely to be geographically diversified and have links to foreign sources of capital or inputs are better positioned to cope with indirect conflict effects than smaller ones, we interact the 2022 dummy with the share of land in the rayon cultivated by producers with operational size above 2,500 ha or between 500 and 2,500 ha. Results, in panel B, support this notion; although none of the farm size groups can entirely eliminate conflict effects, the smallest farm size group is estimated to incur an output loss of about 0.4 tons/ha (coefficient of −0.072) compared to 0.31 tons/ha for medium sized and 0.22 tons/ha for the largest group. As an independent robustness check, we computed NDVI for the area covered by each year's winter cereal mask from Landsat and MODIS imagery instead of Sentinel-2. Except for reinforcing the need to account for time variation in exposure to conflict action, results are consistent though regressions have lower predictive power (R^2 of 0.29 or 0.31) as would be expected if these lower resolution images convey less information (Appendix Table A10 and Table A11).

To put our estimates into context, we compare output losses predicted by our approach to those reported by the EU as well as USAID. Regarding overall magnitudes, the July 2022 USDA/WASDE report projects wheat production in Ukraine at 19.5 million tons, a drop of 13.5 million tons compared to the previous seasons (tables WASDE-626–18 and −19),[34] much larger than the approximately 4.84 million tons obtained in our analysis or 5.9 million tons in the most recent MARS Bulletin (Ben Aoun et al. 2022).[35]

This highlights two points of relevance: First, contrary to more aggregate approaches that are difficult to replicate and cannot be used to assess impacts of exogenous shocks at a granular level, our methodology is based on fields, fully reproducible, and produces estimates of cultivated area and expected output at village council level and by farm size group in a way that can subsequently be compared to actual outcomes to improve model realism and performance, an opportunity that is absent in aggregate approaches. Second, while the reasons for such divergences merit separate investigation, the fact that of the three estimates our micro-data based one is the lowest not only demonstrates the resilience of Ukraine's agricultural sector in the face of adversity but also has implications for the type of support to address the current crisis, the target groups of such support, and estimates of global food supplies.

5. Conclusion and policy implications

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

Beyond providing estimates of direct conflict effects, the ability to provide such information in season at high levels of granularity and update it as new data becomes available can help improve decision-making by policy-makers and private parties to minimize war-induced losses. First, losses could be vastly higher if farmers are unable to harvest the standing crop due to shortages of inputs or unwilling to do so as they would not be able to sell it, e.g., because of a lack of storage space. Information on expected output can help guide efforts to anticipate and avoid such bottlenecks. Second, the data generated allow to identify areas or groups that are particularly affected that may require short-term (working capital) support and, if support can be provided, to

[31] Appendix Fig. A4b presents a scatterplot of mean peak NDVI and yield for 50 equally spaced bins of yield in 2019 and 2020 together with regressions of these for linear, quadratic, and cubic fits (and R^2 and RMSE). Although saturation is not an issue (i.e., a linear regression fits the upper tail reasonably well), higher order polynomials better capture the bottom tail of the yield distribution. In particular, the cubic fit has the highest R^2 and the lowest RMSE.

[32] As per Table 3, there are 377 VCs cultivating an average of 1,678 ha or a total of 632,606 ha and multiplying this figure with 0.073 and then with 0.87 (the share of cereals in winter crop area) yields 40,177 tons of cereals.

[33] Coefficients also suggest that, after adjusting for weather effects NDVI in 2020 and 2021 was less (coefficient of −0.023) and more favorable (0.013) than in 2019 as the excluded category.

[34] https://downloads.usda.library.cornell.edu/usda-esmis/files/3t945q76s/cc08jp14g/cr56p755q/wasde0822.pdf.

[35] The methodology used by WASDE combines MODIS derived growth trends with market information collected by FAS to derive an aggregate estimate of supply in a way that is not easily reproducible. In the absence of clear methodological notes, we can only speculate about the potential reason for this large drop. One possibility could be that the USDA report only counts output harvested on territory under Ukrainian control. Table 5 column 6 indicates that between 1.95 and 1.79 million ha of winter crops are grown on areas that, by end September 2022, were under Russian occupation. With an average yield of 4 t/ha, this would account for some 6.8 million tons, which together with the 4.84 million tons loss estimated here would come close to the 13.5 million tons reported by USDA.

monitor its use and impact. This could help improve not only welfare for local producers but also contribute to greater food security by consumers in countries that are heavily reliant on food imports.

CRediT authorship contribution statement

Klaus Deininger: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing, Funding acquisition. **Daniel Ayalew Ali:** Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Nataliia Kussul:** Methodology, Formal analysis, Writing – review & editing. **Andrii Shelestov:** Methodology, Formal analysis, Software, Writing – review & editing. **Guido Lemoine:** Methodology, Formal analysis, Software, Writing – review & editing. **Hanna Yailimova:** Formal analysis, Software, Writing – review & editing.

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.

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Appendix

Appendix Tables A1-A11

Appendix Fig. A1, Fig. A2, Fig. A3, Fig. A4a, Fig. A4b, Fig. A5.

Table A1
Percent of fields labeled as damaged within different distance ranges from coordinates of ACLED-reported military action.

Time frame	Distance to location of military action based on ACLED data				
	<5 km	5–10 km	10–15 km	15–20 km	greater than20 km
24 Feb – 13 Mar	17.8	20.8	16.1	21.2	24.0
14 Mar – 27 Mar	39.8	34.9	14.4	4.0	6.9
28 Mar – 10 Apr	18.4	20.6	18.8	14.3	27.8
11 Apr – 24 Apr	61.5	21.8	4.6	2.1	10.1
25 Apr – 8 May	53.6	37.6	7.0	1.1	0.7
9 May – 22 May	40.9	33.0	15.8	7.9	2.4
23 May – 5 Jun	63.4	27.9	5.1	2.2	1.4
6 Jun – 19 Jun	51.2	30.2	11.0	5.2	2.4
20 Jun – 3 Jul	75.4	18.9	3.7	1.0	1.0
4 Jul – 17 Jul	59.4	29.4	7.5	2.2	1.4
18 Jul – 31 Jul	64.6	27.2	6.7	0.9	0.6
1 Aug – 14 Aug	54.1	29.0	10.7	2.4	3.8
15–28 Aug	44.6	28.2	12.4	5.3	9.5
29 Aug – 11 Sep	58.0	25.1	10.8	2.6	3.5
12–25 Sep	52.1	29.0	15.2	2.4	1.4
Entire period	54.3	27.8	9.3	3.8	4.8

Source: Own computation from ACLED data on military action and location of damaged fields as described in the text. Note: Distance ranges are mutually exclusive.

Table 6
Predicted direct and indirect effects of conflict on NDVI of winter cereal fields.

	Conflict indicator					
	None	Under occupation	Conflict actions	Troop presence	Any	Conflict intensity
Panel A: Without size interaction						
Conflict indicator		−0.478*	−0.035	0.026	0.001	−1.881***
		(0.246)	(0.270)	(0.223)	(0.221)	(0.297)
Crop damage area (100 ha)	−0.260***	−0.257***	−0.258***	−0.261***	−0.260***	−0.194***
	(0.034)	(0.034)	(0.036)	(0.035)	(0.035)	(0.036)
Year 2020	−2.273***	−2.295***	−2.275***	−2.271***	−2.273***	−2.288***
	(0.352)	(0.352)	(0.352)	(0.352)	(0.352)	(0.352)
Year 2021	1.485***	1.405***	1.480***	1.491***	1.485***	1.266***
	(0.311)	(0.314)	(0.313)	(0.315)	(0.315)	(0.313)
Year 2022	−5.431***	−5.371***	−5.428***	−5.435***	−5.431***	−5.162***
	(0.264)	(0.265)	(0.265)	(0.266)	(0.266)	(0.267)
No. of obs	37,208	37,208	37,208	37,208	37,208	37,208
R-squared	0.361	0.361	0.361	0.361	0.361	0.362
Panel B: With size interaction						
Conflict indicator		−0.500**	0.085	0.030	−0.005	−1.870***
		(0.251)	(0.277)	(0.227)	(0.226)	(0.305)
Damaged area (100 ha)	−0.265***	−0.262***	−0.269***	−0.266***	−0.265***	−0.199***
	(0.036)	(0.036)	(0.038)	(0.037)	(0.038)	(0.038)
Year 2020	−2.452***	−2.478***	−2.448***	−2.450***	−2.453***	−2.462***

(*continued on next page*)

Table 6 (*continued*)

	Conflict indicator					
	None	Under occupation	Conflict actions	Troop presence	Any	Conflict intensity
	(0.357)	(0.357)	(0.357)	(0.357)	(0.357)	(0.357)
Year 2021	1.533***	1.448***	1.544***	1.539***	1.531***	1.317***
	(0.314)	(0.317)	(0.316)	(0.318)	(0.318)	(0.315)
Year 2022	−7.203***	−7.217***	−7.199***	−7.201***	−7.203***	−7.181***
	(0.558)	(0.558)	(0.558)	(0.559)	(0.559)	(0.558)
Yr 2022 # % greater than2500 ha	2.956***	3.028***	2.944***	2.949***	2.957***	3.212***
	(0.593)	(0.594)	(0.594)	(0.595)	(0.595)	(0.594)
Yr 2022 # % 500–2500 ha	1.313*	1.427**	1.300*	1.304*	1.314*	1.626**
	(0.714)	(0.716)	(0.715)	(0.717)	(0.717)	(0.716)
No. of obs	36,684	36,684	36,684	36,684	36,684	36,684
R-squared	0.363	0.363	0.363	0.363	0.363	0.364

Note: Results are from panel regressions with VC fixed effects where the dependent variable is the NDVI for fields planted with winter cereals in each of the relevant years, rescaled between 0 and 100. Crimea and areas occupied since 2014 are excluded. 'Any' is the maximum over the 8 two-week periods considered whereas 'conflict intensity' (col 6) accounts for the temporal dimension by taking a value of 1 for any of the 8 two-week periods when any conflict activity was observed. See Appendix Tables A7 and A8 for tables with all weather-related variables. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table A2
Confusion matrices for crop classification in Ukraine for 2019, 2020, and 2021 Panel A: 2019.

Panel A: 2019

Kappa = 0.94	Artificial	Cereal crops	Rapeseed	Buckwheat	Maize	Sugar beet	Sunflower	Soy	Other crops	Forest	Grassland	Bare land	Water	Wetland	Peas	Alfalfa	Gardens, parks	Grape	UA	F1
Artificial	22567	0	0	0	3	0	0	0	16	0	42	12561	4053	39	0	0	26	220	57.1	70.6
Cereal crops	294	1865708	1355	3795	3548	0	1614	98	5182	0	10318	219	263	36	26334	5729	7926	4422	96.3	97.8
Rapeseed	0	0	464897	5330	0	0	0	0	114	0	0	0	0	0	2734	0	0	630	98.1	98.9
Buckwheat	0	0	0	1823	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100.0	24.0
Maize	10	175	0	163	562293	1546	2469	14863	1008	0	647	9	17	516	173	20	2641	1259	95.7	96.9
Sugar beet	0	1	0	0	136	32510	270	1326	645	0	0	0	0	9	3	0	1	0	93.1	86.6
Sunflower	18	412	0	762	712	4301	792949	10824	2246	0	2	76	0	691	13	340	322	97	97.4	98.2
Soy	0	2662	0	741	4726	1732	2947	143695	1441	0	158	4	0	175	138	1	989	5	90.1	86.9
Other crops	170	397	88	3	82	78	310	14	4796	0	80	374	3550	18	56	0	676	390	43.3	34.4
Forest	439	0	0	0	4	0	0	1	9	87527	43	0	13	427	0	0	16261	0	83.6	91.0
Grassland	234	8558	45	536	1233	0	450	167	580	23	163312	130	312	6380	984	11268	29861	4756	71.4	80.5
Bare land	404	52	0	0	36	0	0	7	1	0	56	16558	4359	4	12	0	268	3	76.1	64.0
Water	14	0	0	0	0	0	0	0	0	0	1	4	773905	114	0	0	0	0	100.0	99.2
Wetland	50	4	0	0	135	0	0	23	12	0	411	3	41	8682	0	0	39	4	92.3	63.5
Peas	0	1	31	0	0	0	0	0	472	0	0	0	0	0	33884	0	0	0	98.5	68.6
Alfalfa	0	531	0	0	0	0	0	0	0	0	15	0	0	9	12	19662	0	0	97.2	68.5
Gardens, parks	166	54	0	197	94	0	184	104	160	192	1746	34	14	820	0	132	54795	13261	76.2	59.0
Grape	32	1	0	4	0	0	10	0	123	0	3	15	5	0	0	0	144	11059	97.0	46.6
PA	92.5	99.3	99.7	13.7	98.1	80.9	99.0	84.0	28.5	99.8	92.4	55.2	98.4	48.4	52.7	52.9	48.1	30.Чер	94.8	

Panel B: 2020

Kappa = 0.89	Cereals	Rapeseed	Maize	Sunflower	Soybeans	Other classes	UA (%)	F1 (%)
Cereals	803,451	5,009	1,464	4,379	17	11,536	97.3	96.2
Rapeseed	118	216,270	307	108	6	2,815	98.5	93.6
Maize	4,219	533	368,090	2,067	8,516	7,611	94.1	91.7
Sunflower	2,932	807	2,577	407,420	4,670	10,744	94.9	94.7
Soybeans	118	0	6,570	2,363	82,478	998	89.1	84.6
Other classes	33,653	19,690	32,479	15,133	6,674	186,046	63.4	72.5
PA (%)	95.1	89.3	89.5	94.4	80.6	84.7	**OA = 91.6%**	

Panel C: 2021

Kappa 0.98	**Cereal**	**Rapeseed**	**Maize**	**Sugar beet**	**Sunflower**	**Soybeans**	**Other crops**	**Other land**	**UA (%)**	**F1 (%)**
Cereal	509,120	246	22	4	152	13	295	621	99.7	99.2
Rapeseed	0	89,007	0	1	0	1	0	0	100	99.2
Maize	50	0	187,650	0	24	4,445	103	264	97.5	98.2
Sugar beet	0	0	3	4237	762	24	15	0	84.1	91.0
Sunflower	731	0	75	1	292,852	3	77	598	99.5	98.9
Soybeans	0	0	424	0	103	50,840	152	47	98.6	93.9
Other crops	4175	1207	278	26	802	1,373	12,930	787	59.9	66.8
Other land	1,747	5	1,302	0	3,419	45	3,578	487,671	98	98.7
PA, (%)	98.7	98.4	98.9	99.3	98.2	89.6	75.4	99.5	**OA = 98.3%**	

Note: PA = producer accuracy; UA = user accuracy; OA = Overall accuracy, F1 = precision recall score.

Table A3
Rayon level farm structure in 2020.

	Total	Crop damage	
		No	Yes
Number of operational farms	72.73	71.27	95.66
Number of farms with 500–2500 ha	12.50	12.30	15.69
Number of farms greater than 2500 ha	6.06	6.00	6.94
Total cultivated land in ha	37,735	37,137	47,120
Share with 500–2500 ha	0.330	0.326	0.385
Share with greater than 2500 ha	0.455	0.455	0.447
Number of Rayons	535	503	32

Source: Own computation based on the State Statistics Service of Ukraine (SSSU) form29.

Table A4
Regressions of winter crop area and NDVI without conflict indicators: 2019–2021.

	Winter crop area	NDVI
GDD, 100°days	320.885***	9.256***
	(18.180)	(0.356)
GDD squared	−13.778***	−0.367***
	(0.727)	(0.011)
Fall rainfall (100 mm)	−302.164***	2.281**
	(50.447)	(0.948)
Winter rainfall (100 mm)	141.254***	9.233***
	(47.410)	(0.779)
Spring rainfall (100 mm)	63.134	0.981
	(45.144)	(0.604)
Fall rainfall squared	265.634***	−0.723
	(34.190)	(0.632)
Winter rainfall squared	−70.333***	−2.014***
	(14.326)	(0.246)
Spring rainfall squared	−76.251***	−0.006
	(22.166)	(0.132)
Fall zero precipitation days	5.488	−0.862***
	(4.089)	(0.062)
Winter zero precipitation days	−1.501	−0.244***
	(1.464)	(0.021)
Spring zero precipitation days	5.575*	0.733***
	(3.290)	(0.047)
Fall zero precipitation days squared	−0.014	0.016***
	(0.061)	(0.001)
Winter zero precipitation days squared	−0.035	0.004***
	(0.033)	(0.000)
Spring zero precipitation days squared	−0.503***	−0.016***
	(0.067)	(0.001)
Constant	−867.482***	23.091***
	(123.134)	(2.832)
No. of obs (village councils)	30,375	27,906
R-squared	0.923	0.673

Note: Results are from linear regression where the dependent variables are winter crop area or NDVI, scaled to fall between 0 and 100. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table A5
Fixed-effects model of conflict effects on winter crop area.

	Conflict indicator					
	None	Under occupation	Conflict actions	Troop presence	Any	Conflict intensity
Conflict indicator		−27.249*	2.074	−48.046***	−51.485***	−94.916***
		(15.705)	(17.026)	(14.009)	(13.933)	(18.708)
Area with crop damage (ha)	−0.137***	−0.135***	−0.138***	−0.116***	−0.111***	−0.100***
	(0.030)	(0.030)	(0.031)	(0.030)	(0.031)	(0.031)
GDD, 100°days	76.033***	79.244***	75.938***	80.846***	81.166***	89.732***
	(19.321)	(19.408)	(19.337)	(19.368)	(19.366)	(19.500)
GDD squared	−3.748***	−3.808***	−3.749***	−3.795***	−3.795***	−4.060***
	(0.674)	(0.675)	(0.674)	(0.674)	(0.674)	(0.677)
Fall rainfall (100 mm)	8.373	10.759	7.999	18.653	19.201	13.996
	(40.431)	(40.453)	(40.549)	(40.535)	(40.529)	(40.430)
Winter rainfall (100 mm)	317.701***	323.896***	317.435***	330.557***	331.413***	334.165***
	(31.933)	(32.131)	(32.008)	(32.147)	(32.141)	(32.084)
Spring rainfall (100 mm)	230.982***	228.923***	231.063***	225.932***	225.665***	227.071***
	(42.107)	(42.122)	(42.113)	(42.125)	(42.122)	(42.097)
Fall rainfall squared	−6.136	−7.076	−5.978	−10.449	−10.528	−6.837
	(28.455)	(28.459)	(28.485)	(28.478)	(28.474)	(28.444)
Winter rainfall squared	−54.468***	−55.379***	−54.434***	−56.338***	−56.447***	−56.728***
	(8.654)	(8.670)	(8.659)	(8.670)	(8.669)	(8.662)
Spring rainfall squared	−138.185***	−135.758***	−138.314***	−131.672***	−131.237***	−132.898***
	(20.708)	(20.755)	(20.735)	(20.791)	(20.789)	(20.726)
Fall zero precipitation days	59.101***	58.867***	59.101***	58.744***	58.701***	58.131***
	(3.802)	(3.804)	(3.802)	(3.802)	(3.802)	(3.805)
Winter zero precipitation days	1.796	2.103	1.779	2.550	2.632	2.579
	(1.684)	(1.693)	(1.690)	(1.698)	(1.699)	(1.690)
Spring zero precipitation days	−0.650	0.005	−0.681	0.825	0.953	1.201
	(3.031)	(3.055)	(3.042)	(3.061)	(3.062)	(3.052)
Fall zero precip. days squared	−0.857***	−0.856***	−0.857***	−0.856***	−0.855***	−0.849***
	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)
W. zero precip. days squared	−0.098***	−0.100***	−0.098***	−0.104***	−0.104***	−0.102***
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)

(*continued on next page*)

Table A5 (*continued*)

	Conflict indicator					
	None	Under occupation	Conflict actions	Troop presence	Any	Conflict intensity
S. zero precip. days squared	−0.288***	−0.296***	−0.288***	−0.308***	−0.310***	−0.309***
	(0.064)	(0.065)	(0.064)	(0.065)	(0.065)	(0.064)
Year 2020	87.085***	77.504***	87.546***	67.161***	65.310**	56.513**
	(24.779)	(25.386)	(25.067)	(25.447)	(25.465)	(25.491)
Year 2021	46.265**	44.750**	46.360**	41.301**	40.628**	42.893**
	(20.473)	(20.491)	(20.488)	(20.520)	(20.525)	(20.475)
Year 2022	−101.168***	−95.792***	−101.477***	−89.024***	−87.918***	−82.129***
	(13.864)	(14.206)	(14.094)	(14.307)	(14.318)	(14.358)
Constant	−738.941***	−781.881***	−736.838***	−824.198***	−830.580***	−886.955***
	(167.375)	(169.189)	(168.266)	(169.182)	(169.168)	(169.831)
No. of obs	40,500	40,500	40,500	40,500	40,500	40,500
R-squared	0.095	0.095	0.095	0.095	0.095	0.096

Note: Results are from 2019 to 2022 panel regressions where the unit of observation is the village council. The dependent variable is the area covered with winter crops as of May 1 of the relevant year. Crimea and areas that have been occupied since 2014 are excluded. GDD is cumulative growing degree days above 0 °C between October 1and April 30 approximated hourly by sinusoidal distribution of minimum and maximum temperature (d'Agostino and Schlenker, 2016); and fall, winter and spring months are Oct-Nov, Dec-Feb, and Mar-Apr, respectively. 'Any' (Col. 5) is the maximum over the 4 two-week periods considered whereas 'conflict intensity' (col 6) accounts for the temporal dimension by taking a value of 1 for any of the 4 two-week periods when any conflict activity was observed. See Appendix Table A1 for full specification including weather variables. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table A6

Results from fixed-effects regression for winter crop area after ground truth data collection for 2022.

	Conflict indicator					
	None	**Under occupation**	**Conflict actions**	**Troop presence**	**Any**	**Conflict intensity**
Conflict indicator		−41.708***	−4.730	−58.746***	−61.732***	−113.611***
		(15.598)	(16.910)	(13.913)	(13.838)	(18.578)
Area with crop damage (ha)	−0.131***	−0.129***	−0.129***	−0.106***	−0.100***	−0.087***
	(0.030)	(0.030)	(0.031)	(0.030)	(0.030)	(0.030)
GDD, 100°days	82.248***	87.162***	82.465***	88.132***	88.401***	98.644***
	(19.190)	(19.276)	(19.206)	(19.235)	(19.233)	(19.365)
GDD squared	−3.689***	−3.781***	−3.689***	−3.747***	−3.745***	−4.062***
	(0.670)	(0.671)	(0.670)	(0.670)	(0.670)	(0.672)
Fall rainfall (100 mm)	10.627	14.278	11.480	23.197	23.610	17.358
	(40.158)	(40.177)	(40.274)	(40.257)	(40.251)	(40.149)
Winter rainfall (100 mm)	305.530***	315.013***	306.137***	321.250***	321.971***	325.237***
	(31.717)	(31.912)	(31.792)	(31.926)	(31.921)	(31.861)
Spring rainfall (100 mm)	225.950***	222.799***	225.766***	219.775***	219.575***	221.269***
	(41.822)	(41.834)	(41.828)	(41.836)	(41.833)	(41.804)
Fall rainfall squared	−5.142	−6.582	−5.501	−10.417	−10.409	−5.982
	(28.263)	(28.265)	(28.292)	(28.282)	(28.278)	(28.246)
Winter rainfall squared	−50.319***	−51.715***	−50.397***	−52.606***	−52.692***	−53.024***
	(8.596)	(8.611)	(8.600)	(8.610)	(8.610)	(8.602)
Spring rainfall squared	−139.128***	−135.412***	−138.835***	−131.163***	−130.797***	−132.798***
	(20.568)	(20.613)	(20.595)	(20.649)	(20.646)	(20.582)
Fall zero precipitation days	57.806***	57.449***	57.806***	57.371***	57.327***	56.645***
	(3.776)	(3.778)	(3.776)	(3.776)	(3.776)	(3.778)
Winter zero precipitation days	2.746	3.216*	2.785*	3.668**	3.749**	3.683**
	(1.673)	(1.682)	(1.678)	(1.686)	(1.687)	(1.679)
Spring zero precipitation days	−1.315	−0.312	−1.245	0.489	0.608	0.901
	(3.011)	(3.034)	(3.021)	(3.040)	(3.041)	(3.031)
Fall zero precip. days squared	−0.820***	−0.817***	−0.820***	−0.817***	−0.817***	−0.809***
	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)
W. zero precip. days squared	−0.123***	−0.126***	−0.123***	−0.129***	−0.130***	−0.128***
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
S. zero precip. days squared	−0.288***	−0.300***	−0.289***	−0.312***	−0.314***	−0.313***
	(0.064)	(0.064)	(0.064)	(0.064)	(0.064)	(0.064)
Year 2020	69.214***	54.550**	68.162***	44.853*	43.105*	32.620
	(24.611)	(25.213)	(24.897)	(25.272)	(25.290)	(25.314)
Year 2021	54.597***	52.277**	54.380***	48.527**	47.838**	50.560**
	(20.334)	(20.351)	(20.350)	(20.380)	(20.385)	(20.333)
Year 2022	−129.707***	−121.478***	−129.003***	−114.859***	−113.820***	−106.919***
	(13.771)	(14.109)	(13.999)	(14.209)	(14.220)	(14.258)
Constant	−793.412***	−859.136***	−798.208***	−897.657***	−903.289***	−970.580***
	(166.243)	(168.034)	(167.128)	(168.021)	(168.007)	(168.651)
No. of obs (village councils)	40,500	40,500	40,500	40,500	40,500	40,500
R-squared	0.100	0.100	0.100	0.100	0.100	0.101

Note: Results are from 2019 to 2022 panel regressions where the unit of observation is the village council. The dependent variable is the area covered with winter crops as of May 1 of the relevant year. Crimea and areas that have been occupied since 2014 are excluded. GDD is cumulative growing degree days above 0 °C between October 1and April 30 approximated hourly by sinusoidal distribution of minimum and maximum temperature (d'Agostino and Schlenker, 2016); and fall, winter and spring months are Oct-Nov, Dec-Feb, and Mar-Apr, respectively. 'Any' (Col. 5) is the maximum over the 4 two-week periods considered whereas 'conflict intensity' (col 6) accounts for the temporal dimension by taking a value of 1 for any of the 4 two-week periods when any conflict activity was observed. See Appendix Table A1 for full specification including weather variables. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table A7
Predicted direct and indirect effects of conflict on NDVI of winter cereal fields.

	Conflict indicator					
	None	Under occupation	Conflict actions	Troop presence	Any	Conflict intensity
Conflict indicator		−0.478*	−0.035	0.026	0.001	−1.881***
		(0.246)	(0.270)	(0.223)	(0.221)	(0.297)
Area crop damage (100 ha)	−0.260***	−0.257***	−0.258***	−0.261***	−0.260***	−0.194***
	(0.034)	(0.034)	(0.036)	(0.035)	(0.035)	(0.036)
GDD, 100°days	8.688***	8.708***	8.686***	8.689***	8.688***	8.950***
	(0.260)	(0.260)	(0.261)	(0.260)	(0.260)	(0.263)
GDD squared	−0.316***	−0.317***	−0.316***	−0.316***	−0.316***	−0.326***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Fall rainfall (100 mm)	7.840***	7.773***	7.842***	7.841***	7.840***	7.484***
	(0.686)	(0.687)	(0.687)	(0.687)	(0.687)	(0.688)
Winter rainfall (100 mm)	5.483***	5.542***	5.485***	5.479***	5.483***	5.612***
	(0.544)	(0.544)	(0.544)	(0.544)	(0.544)	(0.544)
Spring rainfall (100 mm)	1.209**	1.342***	1.214**	1.200**	1.209**	1.673***
	(0.502)	(0.507)	(0.504)	(0.508)	(0.508)	(0.507)
Fall rainfall squared	−3.621***	−3.579***	−3.622***	−3.622***	−3.621***	−3.383***
	(0.477)	(0.477)	(0.477)	(0.477)	(0.477)	(0.478)
Winter rainfall squared	−1.187***	−1.199***	−1.188***	−1.186***	−1.187***	−1.209***
	(0.152)	(0.152)	(0.152)	(0.153)	(0.153)	(0.152)
Spring rainfall squared	−0.039	−0.060	−0.040	−0.037	−0.039	−0.118
	(0.114)	(0.114)	(0.114)	(0.114)	(0.114)	(0.114)
Fall zero precipitation days	−0.714***	−0.717***	−0.714***	−0.714***	−0.714***	−0.730***
	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)
Winter zero precipitation days	−0.037	−0.034	−0.037	−0.037	−0.037	−0.035
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Spring zero precipitation days	0.635***	0.633***	0.635***	0.635***	0.635***	0.611***
	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.042)
Fall zero precip. days squared	0.014***	0.014***	0.014***	0.014***	0.014***	0.015***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
W. zero precip. days squared	−0.00012	−0.00011	−0.00012	−0.00012	−0.00012	0.00002
	(0.00047)	(0.00047)	(0.00047)	(0.00047)	(0.00047)	(0.00047)
S. zero precip. days squared	−0.013***	−0.013***	−0.013***	−0.013***	−0.013***	−0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year 2020	−2.273***	−2.295***	−2.275***	−2.271***	−2.273***	−2.288***
	(0.352)	(0.352)	(0.352)	(0.352)	(0.352)	(0.352)
Year 2021	1.485***	1.405***	1.480***	1.491***	1.485***	1.266***
	(0.311)	(0.314)	(0.313)	(0.315)	(0.315)	(0.313)
Year 2022	−5.431***	−5.371***	−5.428***	−5.435***	−5.431***	−5.162***
	(0.264)	(0.265)	(0.265)	(0.266)	(0.266)	(0.267)
Constant	15.668***	15.521***	15.674***	15.665***	15.667***	14.072***
	(3.112)	(3.112)	(3.112)	(3.112)	(3.112)	(3.120)
No. of obs (village councils)	37,208	37,208	37,208	37,208	37,208	37,208
R-squared	0.361	0.361	0.361	0.361	0.361	0.362

Note: Results are from 2019 to 2022 panel regressions where the unit of observation is the village council and the dependent variable is the NDVI for fields planted with winter cereals in each of the relevant years, rescaled between 0 and 100. Crimea and areas that have been occupied since 2014 are excluded. GDD is cumulative growing degree days above 0 °C between October 1and May 31 approximated hourly by sinusoidal distribution of minimum and maximum temperature (d'Agostino and Schlenker, 2016); and fall, winter and spring months are Oct-Nov, Dec-Feb, and Mar-May, respectively. 'Any' (Col. 5) is the maximum over the 8 two-week periods considered whereas 'conflict intensity' (col 6) accounts for the temporal dimension by taking a value of 1 for any of the 8 two-week periods when any conflict activity was observed. See Appendix Table A1 for full specification including weather variables. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table A8
Predicted direct and indirect effects of conflict on NDVI of winter cereal fields.

	Conflict indicator					
	None	Under occupation	Conflict actions	Troop presence	Any	Conflict intensity
Conflict indicator		−0.500**	0.085	0.030	−0.005	−1.870***
		(0.251)	(0.277)	(0.227)	(0.226)	(0.305)
Area with crop damage (100 ha)	−0.265***	−0.262***	−0.269***	−0.266***	−0.265***	−0.199***
	(0.036)	(0.036)	(0.038)	(0.037)	(0.038)	(0.038)
GDD, 100°days	9.025***	9.046***	9.029***	9.025***	9.025***	9.285***
	(0.265)	(0.266)	(0.266)	(0.266)	(0.266)	(0.269)
GDD squared	−0.324***	−0.326***	−0.325***	−0.324***	−0.324***	−0.334***
	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)
Fall rainfall (100 mm)	8.078***	8.017***	8.070***	8.079***	8.078***	7.741***
	(0.694)	(0.695)	(0.695)	(0.694)	(0.694)	(0.696)
Winter rainfall (100 mm)	4.891***	4.939***	4.888***	4.888***	4.891***	4.961***
	(0.558)	(0.558)	(0.558)	(0.558)	(0.558)	(0.558)
Spring rainfall (100 mm)	1.215**	1.358***	1.202**	1.204**	1.217**	1.679***
	(0.508)	(0.513)	(0.510)	(0.514)	(0.514)	(0.513)
Fall rainfall squared	−3.743***	−3.706***	−3.739***	−3.743***	−3.742***	−3.521***
	(0.483)	(0.483)	(0.483)	(0.483)	(0.483)	(0.484)
Winter rainfall squared	−1.022***	−1.030***	−1.022***	−1.022***	−1.023***	−1.029***
	(0.156)	(0.156)	(0.156)	(0.156)	(0.156)	(0.156)
Spring rainfall squared	−0.043	−0.067	−0.041	−0.042	−0.044	−0.124
	(0.115)	(0.116)	(0.115)	(0.116)	(0.116)	(0.116)
Fall zero precipitation days	−0.751***	−0.754***	−0.751***	−0.750***	−0.751***	−0.768***
	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)
Winter zero precipitation days	−0.028	−0.025	−0.029	−0.029	−0.028	−0.026
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Spring zero precipitation days	0.641***	0.639***	0.641***	0.641***	0.641***	0.617***
	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)
Fall zero precip. days squared	0.015***	0.015***	0.015***	0.015***	0.015***	0.015***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
W. zero precip. days squared	−0.00026	−0.00025	−0.00026	−0.00026	−0.00026	−0.00012
	(0.00047)	(0.00047)	(0.00047)	(0.00047)	(0.00047)	(0.00047)
S. zero precip. days squared	−0.013***	−0.013***	−0.013***	−0.013***	−0.013***	−0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year 2020	−2.452***	−2.478***	−2.448***	−2.450***	−2.453***	−2.462***
	(0.357)	(0.357)	(0.357)	(0.357)	(0.357)	(0.357)
Year 2021	1.533***	1.448***	1.544***	1.539***	1.531***	1.317***
	(0.314)	(0.317)	(0.316)	(0.318)	(0.318)	(0.315)
Year 2022	−7.203***	−7.217***	−7.199***	−7.201***	−7.203***	−7.181***
	(0.558)	(0.558)	(0.558)	(0.559)	(0.559)	(0.558)
Year 2022 # % greater than2500 ha	2.956***	3.028***	2.944***	2.949***	2.957***	3.212***
	(0.593)	(0.594)	(0.594)	(0.595)	(0.595)	(0.594)
Year 2022 # % 500–2500 ha	1.313*	1.427**	1.300*	1.304*	1.314*	1.626**
	(0.714)	(0.716)	(0.715)	(0.717)	(0.717)	(0.716)
Constant	13.322***	13.173***	13.301***	13.319***	13.323***	11.820***
	(3.138)	(3.139)	(3.139)	(3.138)	(3.138)	(3.145)
No. of obs (village councils)	36,684	36,684	36,684	36,684	36,684	36,684
R-squared	0.363	0.363	0.363	0.363	0.363	0.364

Note: Results are from 2019 to 2022 panel regressions where the unit of observation is the village council and the dependent variable is the NDVI for fields planted with winter cereals in each of the relevant years, rescaled between 0 and 100. Crimea and areas that have been occupied since 2014 are excluded. GDD is cumulative growing degree days above 0 °C between October 1and May 31 approximated hourly by sinusoidal distribution of minimum and maximum temperature (d'Agostino and Schlenker, 2016); and fall, winter and spring months are Oct-Nov, Dec-Feb, and Mar-May, respectively. 'Any' (Col. 5) is the maximum over the 8 two-week periods considered whereas 'conflict intensity' (col 6) accounts for the temporal dimension by taking a value of 1 for any of the 8 two-week periods when any conflict activity was observed. See Appendix Table A1 for full specification including weather variables. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table A9
Relationship between winter wheat yield and NDVI at village level: 2019–2020.

	Village fixed effects included?	
	Yes	No
NDVI	−29.624***	−24.213***
	(7.272)	(7.805)
NDVI squared	46.360***	40.466***
	(10.643)	(11.417)
NDVI cubed	−20.257***	−16.194***
	(5.077)	(5.447)
Year 2020	−0.099***	0.166***
	(0.025)	(0.030)
Constant	8.566***	5.765***
	(1.615)	(1.735)
No. of obs (village councils)	8,634	8,634
R-squared	0.828	0.246

Note: The table reports results from a linear regression of the yield of winter wheat (tons/ha) at village council level. Data are from the State Statistics Service of Ukraine (form 29) for the years 2019 and 2020. Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table A10
Predicted direct and indirect effects of conflict on Landsat NDVI of winter cereal fields at VC level.

	Conflict indicator					
	None	Under occupation	Conflict actions	Troop presence	Conflict intensity	Any
Conflict indicator		0.284	−0.835***	−0.273	−0.349	−0.611*
		(0.266)	(0.291)	(0.241)	(0.240)	(0.318)
Area with crop damage (100 ha)	−0.220***	−0.222***	−0.186***	−0.210***	−0.204***	−0.199***
	(0.036)	(0.036)	(0.038)	(0.037)	(0.038)	(0.038)
GDD, 100°days	9.718***	9.703***	9.673***	9.713***	9.710***	9.805***
	(0.288)	(0.289)	(0.289)	(0.288)	(0.288)	(0.292)
GDD squared	−0.338***	−0.337***	−0.337***	−0.338***	−0.338***	−0.341***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Fall rainfall (100 mm)	8.794***	8.833***	8.889***	8.791***	8.785***	8.689***
	(0.784)	(0.785)	(0.784)	(0.784)	(0.784)	(0.786)
Winter rainfall (100 mm)	6.899***	6.865***	6.942***	6.933***	6.942***	6.949***
	(0.626)	(0.627)	(0.626)	(0.627)	(0.627)	(0.627)
Spring rainfall (100 mm)	−5.001***	−5.082***	−4.866***	−4.902***	−4.873***	−4.843***
	(0.565)	(0.570)	(0.567)	(0.572)	(0.572)	(0.571)
Fall rainfall squared	−5.785***	−5.810***	−5.826***	−5.778***	−5.772***	−5.712***
	(0.553)	(0.553)	(0.553)	(0.553)	(0.553)	(0.554)
Winter rainfall squared	−0.583***	−0.576***	−0.591***	−0.590***	−0.592***	−0.590***
	(0.180)	(0.180)	(0.180)	(0.180)	(0.180)	(0.180)
Spring rainfall squared	1.394***	1.408***	1.370***	1.377***	1.372***	1.366***
	(0.130)	(0.131)	(0.130)	(0.131)	(0.131)	(0.131)
Fall zero precipitation days	−0.456***	−0.455***	−0.454***	−0.456***	−0.456***	−0.461***
	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)
Winter zero precipitation days	0.005	0.003	0.010	0.007	0.008	0.006
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
Spring zero precipitation days	0.383***	0.385***	0.384***	0.382***	0.381***	0.374***
	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)
Fall zero precip. days squared	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
W. zero precip. days squared	−0.001**	−0.001**	−0.001**	−0.001**	−0.001**	−0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
S. zero precip. days squared	−0.008***	−0.008***	−0.008***	−0.008***	−0.008***	−0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year 2020	0.387	0.398	0.345	0.371	0.365	0.380
	(0.390)	(0.390)	(0.390)	(0.390)	(0.390)	(0.390)
Year 2021	1.246***	1.293***	1.133***	1.181***	1.159***	1.170***
	(0.339)	(0.341)	(0.341)	(0.343)	(0.344)	(0.341)
Year 2022	−4.321***	−4.360***	−4.250***	−4.278***	−4.265***	−4.229***
	(0.288)	(0.290)	(0.289)	(0.290)	(0.290)	(0.292)
Constant	11.103***	11.211***	11.297***	11.125***	11.146***	10.551***
	(3.426)	(3.427)	(3.426)	(3.426)	(3.426)	(3.438)
No. of obs (village councils)	32,344	32,344	32,344	32,344	32,344	32,344
R-squared	0.308	0.308	0.308	0.308	0.308	0.308

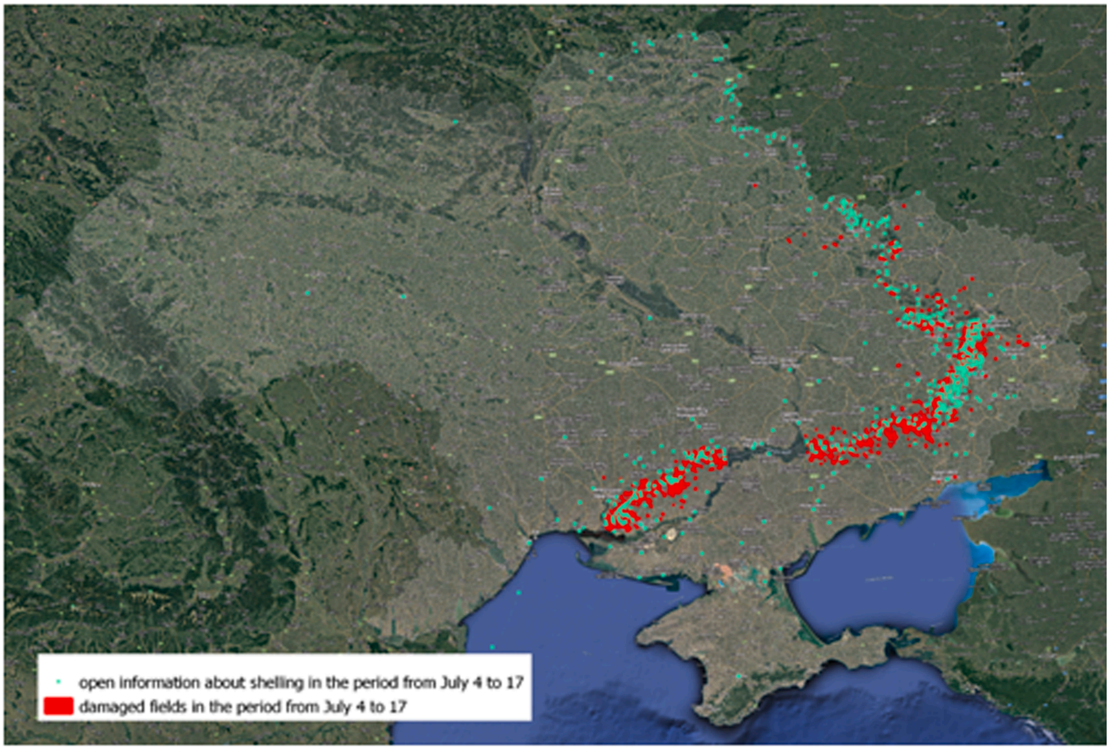
Note: Results are from 2019 to 2022 panel regressions where the unit of observation is the village council and the dependent variable is the NDVI from Landsat for fields planted with winter cereals in each of the relevant years, rescaled between 0 and 100. Crimea and areas that have been occupied since 2014 are excluded. GDD is cumulative growing degree days above 0 °C between October 1and May 31 approximated hourly by sinusoidal distribution of minimum and maximum temperature (d'Agostino and Schlenker, 2016); and fall, winter and spring months are Oct-Nov, Dec-Feb, and Mar-May, respectively. 'Any' (Col. 5) is the maximum over the 8 two-week periods considered whereas 'conflict intensity' (col 6) accounts for the temporal dimension by taking a value of 1 for any of the 8 two-week periods when any conflict activity was observed. See Appendix Table A1 for full specification including weather variables. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Table A11
Predicted direct and indirect effects of conflict on MODIS NDVI of winter cereal fields at VC level.

	Conflict indicator					
	None	Under occupation	Conflict actions	Troop presence	Conflict intensity	Any
Conflict indicator		0.245	−0.051	0.481**	0.442**	−0.855***
		(0.214)	(0.235)	(0.193)	(0.192)	(0.258)
Area with crop damage (100 ha)	−0.160***	−0.161***	−0.157***	−0.178***	−0.180***	−0.130***
	(0.030)	(0.030)	(0.031)	(0.030)	(0.031)	(0.031)
GDD, 100°days	7.873***	7.863***	7.870***	7.886***	7.886***	7.992***
	(0.226)	(0.226)	(0.226)	(0.226)	(0.226)	(0.229)
GDD squared	−0.254***	−0.253***	−0.254***	−0.253***	−0.253***	−0.258***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Fall rainfall (100 mm)	6.610***	6.644***	6.614***	6.628***	6.632***	6.448***
	(0.596)	(0.597)	(0.596)	(0.596)	(0.596)	(0.598)
Winter rainfall (100 mm)	6.780***	6.750***	6.783***	6.716***	6.722***	6.839***
	(0.472)	(0.473)	(0.472)	(0.473)	(0.473)	(0.472)
Spring rainfall (100 mm)	−3.010***	−3.079***	−3.002***	−3.179***	−3.167***	−2.799***
	(0.436)	(0.440)	(0.438)	(0.441)	(0.441)	(0.441)
Fall rainfall squared	−3.751***	−3.772***	−3.752***	−3.770***	−3.773***	−3.643***
	(0.414)	(0.414)	(0.414)	(0.414)	(0.414)	(0.415)
Winter rainfall squared	−1.371***	−1.364***	−1.371***	−1.355***	−1.357***	−1.381***
	(0.132)	(0.132)	(0.132)	(0.132)	(0.132)	(0.132)
Spring rainfall squared	0.695***	0.706***	0.693***	0.722***	0.720***	0.659***
	(0.099)	(0.099)	(0.099)	(0.099)	(0.099)	(0.099)
Fall zero precipitation days	−0.244***	−0.243***	−0.244***	−0.243***	−0.243***	−0.251***
	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)
Winter zero precipitation days	−0.033	−0.035	−0.033	−0.038*	−0.038*	−0.032
	(0.022)	(0.022)	(0.023)	(0.023)	(0.023)	(0.022)
Spring zero precipitation days	0.347***	0.348***	0.347***	0.348***	0.348***	0.336***
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
Fall zero precip. days squared	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
W. zero precip. days squared	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
S. zero precip. days squared	−0.009***	−0.009***	−0.009***	−0.009***	−0.009***	−0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year 2020	−1.086***	−1.075***	−1.089***	−1.052***	−1.055***	−1.093***
	(0.305)	(0.306)	(0.306)	(0.306)	(0.306)	(0.305)
Year 2021	2.737***	2.778***	2.730***	2.849***	2.844***	2.637***
	(0.270)	(0.272)	(0.272)	(0.274)	(0.274)	(0.272)
Year 2022	−1.994***	−2.025***	−1.990***	−2.067***	−2.063***	−1.872***
	(0.229)	(0.231)	(0.230)	(0.231)	(0.231)	(0.232)
Constant	12.896***	12.971***	12.906***	12.851***	12.838***	12.171***
	(2.702)	(2.703)	(2.703)	(2.702)	(2.702)	(2.710)
No. of obs (village councils)	37,248	37,248	37,248	37,248	37,248	37,248
R-squared	0.287	0.287	0.287	0.287	0.287	0.287

Note: Results are from 2019 to 2022 panel regressions where the unit of observation is the village council and the dependent variable is the NDVI from MODIS for fields planted with winter cereals in each of the relevant years, rescaled between 0 and 100. Crimea and areas that have been occupied since 2014 are excluded. GDD is cumulative growing degree days above 0 °C between October 1and May 31 approximated hourly by sinusoidal distribution of minimum and maximum temperature (d'Agostino and Schlenker, 2016); and fall, winter and spring months are Oct-Nov, Dec-Feb, and Mar-May, respectively. 'Any' (Col. 5) is the maximum over the 8 two-week periods considered whereas 'conflict intensity' (col 6) accounts for the temporal dimension by taking a value of 1 for any of the 8 two-week periods when any conflict activity was observed. See Appendix Table A1 for full specification including weather variables. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

Panel A: National overview



Panel B: Detailed example (Velyka Novosilka city, Donetsk oblast)

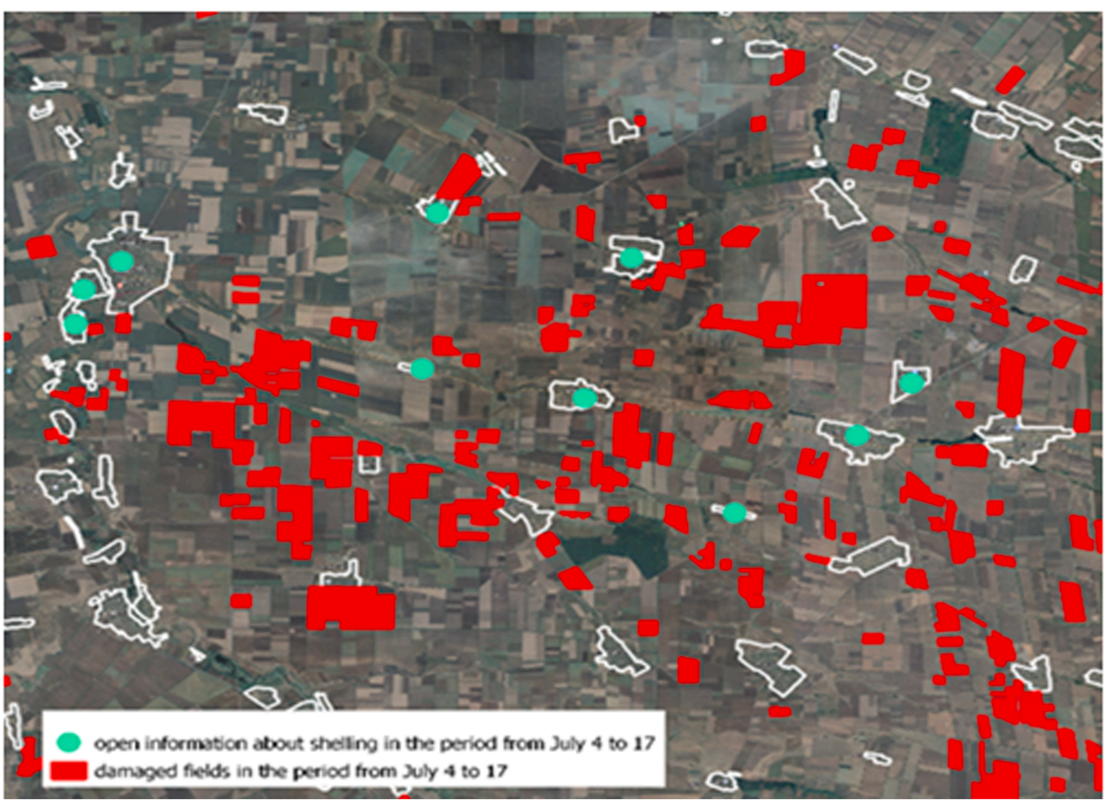


Fig. A1. Comparing location of damaged fields determined based on Satellite imagery to locations of military action based on ACLED data.

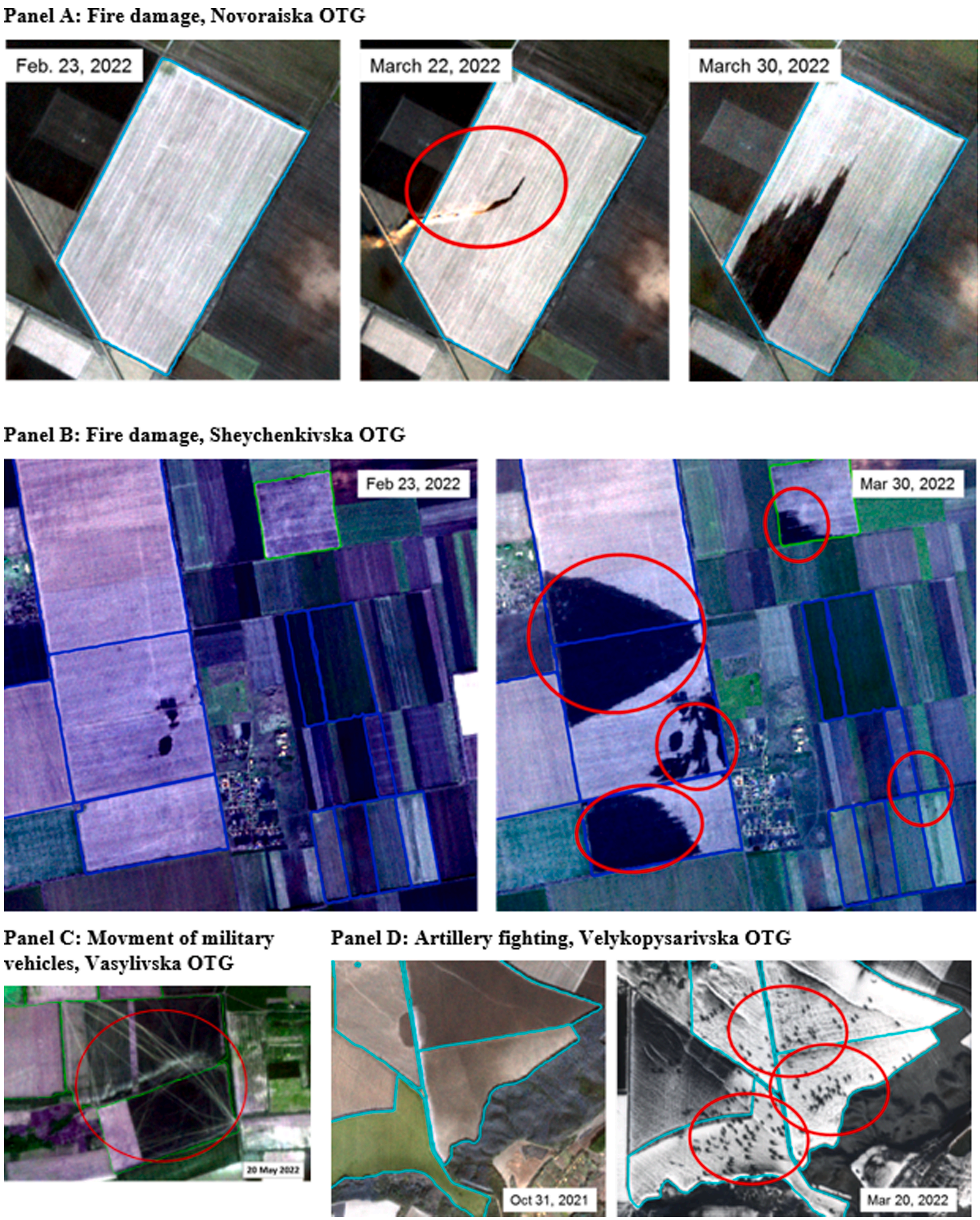


Fig. A2. Examples of most frequent types of field damages.

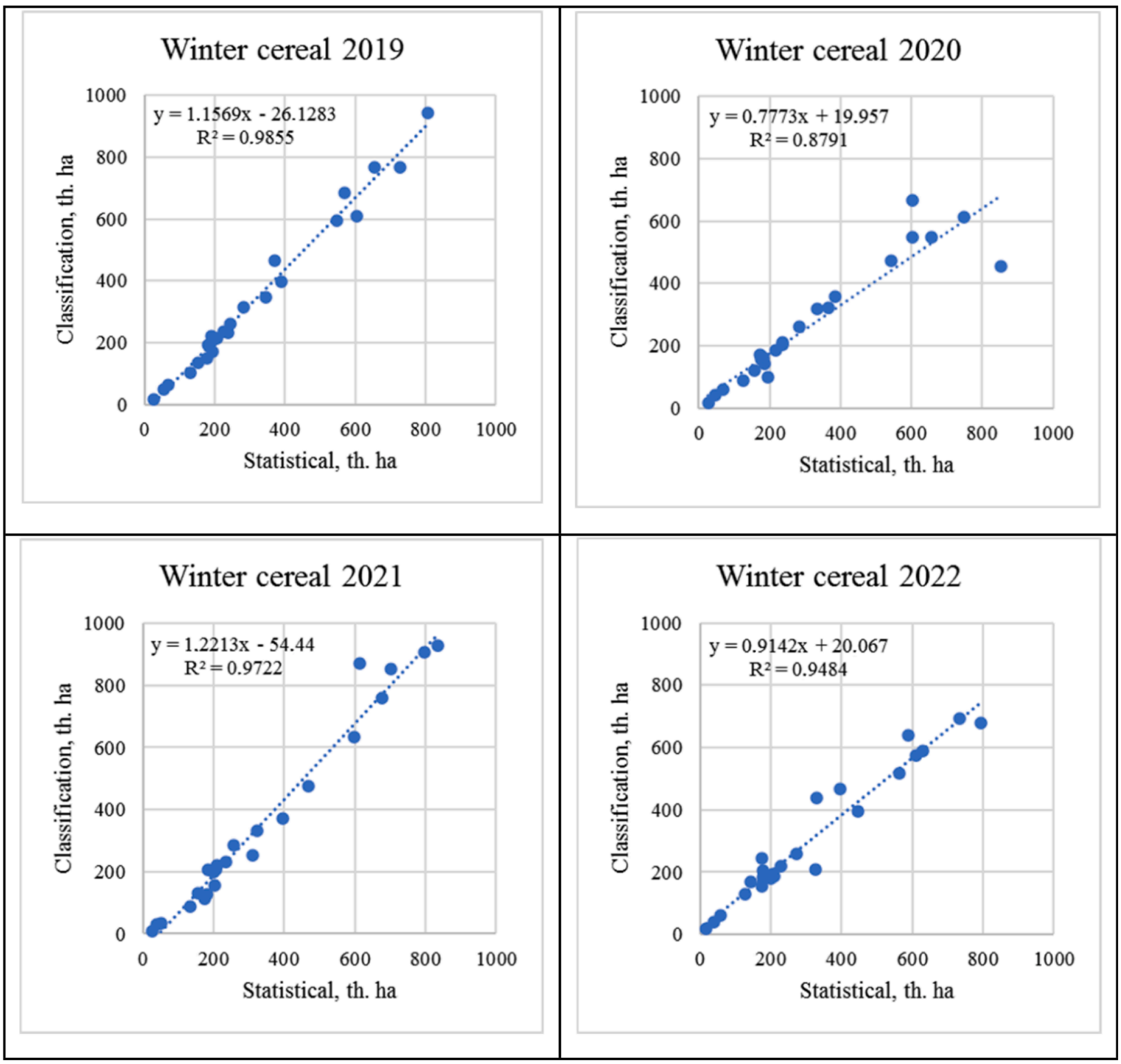


Fig. A3. Comparison of winter cereal area based on interpretation of remote sensing to official statistics at oblast level.

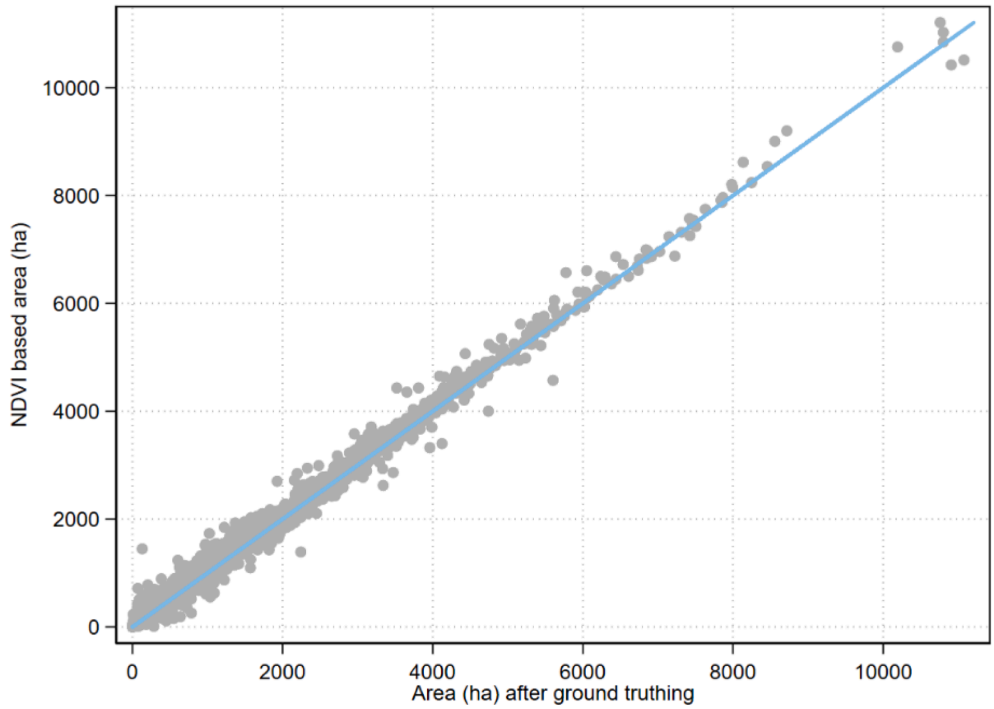


Fig. A4a. Comparison of village-level winter crop area based on NDVI segmentation on May 1 vs ground truthed data, 2022.

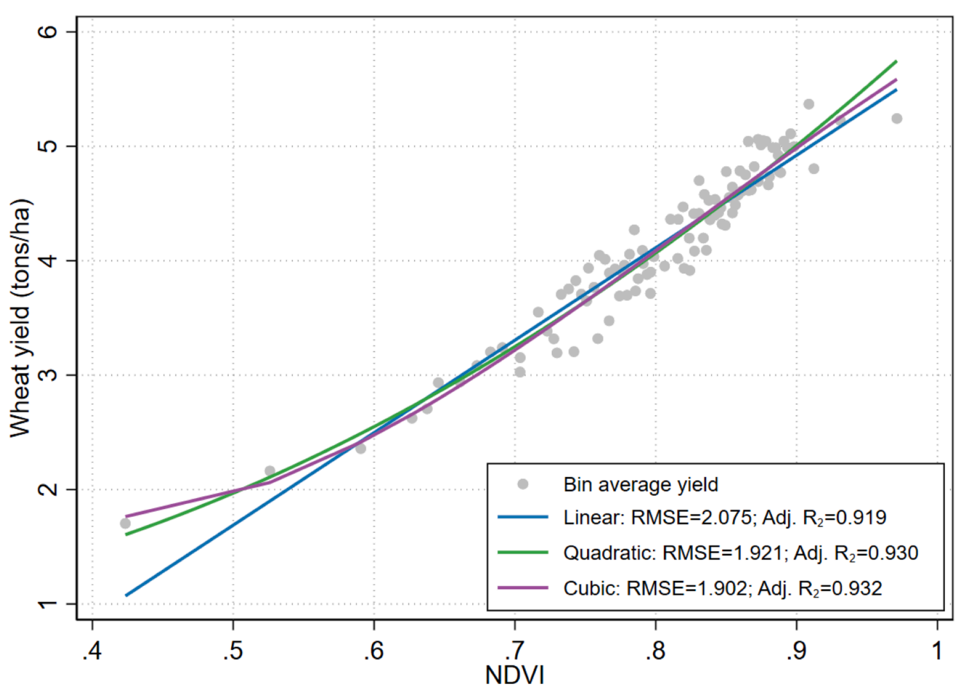


Fig. A4b. Relationship between winter wheat yield and peak NDVI: 2019–2020 Note: For each of the two years, we classify yield in 50 equally spaced bins and link these to the associated NDVI.

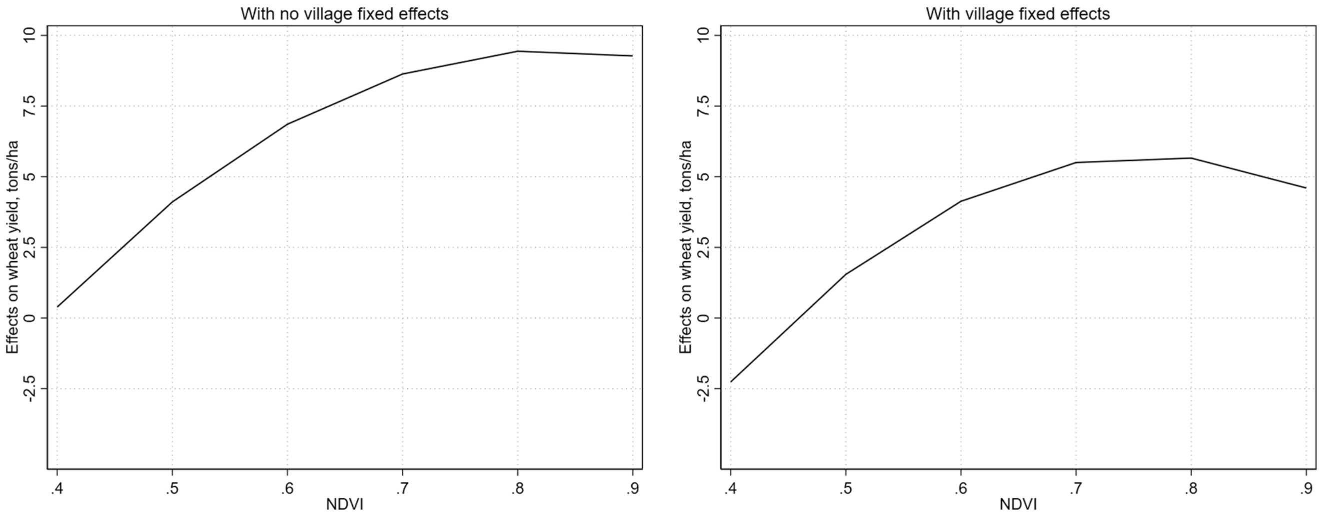


Fig. A5. Predicted marginal effects of peak NDVI on wheat yield for Ukraine Source: Computed based on coefficients estimated in Appendix Table A9.

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