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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

This paper uses a 4-year panel (2019–2022) of 10,125 village councils in Ukraine to estimate direct and indirect effects of the war started by Russia on area and expected yield of winter crops. 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 9.14 rather than 8.38 mn. ha, a 0.75 mn. ha reduction, 86% of which is due to economy-wide effects. The estimated conflict-induced drop in NDVI for winter cereal, which is particularly pronounced for small farms, translates into a 15% yield reduction or an output loss of 4.2 million tons. Taking area and yield reduction together suggests a war-induced loss of winter crop output of 20% if the current winter crop can be harvested fully.

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1. Introduction

More than four months into the war that started with Russia's attack on Ukraine on Feb. 24, 2022, the human and economic toll is already vast: 6 and 8 million individuals are estimated to have left the country or be internally displaced requiring support and GDP is estimated to contract by 45%. Implications for regional and global food security will be far-reaching as, with 41.5 million ha of highly fertile land–larger than the agricultural area of France (18. mn ha), Germany (12 mn. ha) and Poland (11 mn. ha) combined–Ukraine has traditionally been 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 alternatives with comparable capacity prevents Ukraine from exporting most of its 2021 harvest, 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 harvest this creates, together with war-induced shortages of inputs such as fuel, fertilizer, seed, or labor, may affect farmers' planting and crop management decisions in the 2022 season. This would depress not only local welfare but also imply that, instead of realizing its vast potential for intensification of wheat production (Swinnen *et al.* 2017), production losses in Ukraine will exacerbate global food insecurity.

To quantify war-induced direct and indirect impacts on area and expected yield of winter crops, this paper uses 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 for each of these years is available. To generate a measure of war-related disturbances that is more relevant for agriculture than the measures normally used in the literature, 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 from changes on repeat imagery by medium-resolution optical sensors (Sentinel-2 and Planet). Sample images are displayed in the appendix.

We then apply panel econometric methods to provide estimates of war effects on two outcome variables, namely (i) the extent of area grown with winter crops; and (ii) for winter crop fields, peak NDVI as a predictor of crop yield, both at VC level. Estimates of direct effects are obtained from the coefficients on war-related disturbances (damaged agricultural fields or conflict indicators) that we include as independent variables. Village fixed effects are then used to control for time invariant effects (e.g., soil quality, infrastructure access, or social cohesion and effectiveness of local leadership) and data on precipitation and accumulated temperature control for time varying effects, a 2022 dummy can be interpreted as an upper bound estimate of indirect conflict effects.

Our key finding is that direct conflict effects are relatively modest but that they are dwarfed by indirect ones: Conflict reduced the area grown with winter crops by up to 0.755 million ha, 88.4% of which due to indirect effects. On winter wheat fields, changes in NDVI suggest a conflict-induced drop in yield of up to 1.5%, a loss of 4.7 mn. t of which 4.4 mn t. are attributable to indirect and 0.3 mn. t to direct effects. Findings are robust across a range of alternative sensors (Landsat and MODIS). Also, expected winter wheat yields drop most in rayons 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 prevalent in developing countries is one where shocks to food production–or the value of agricultural endowments more generally–trigger conflict. We show that a case like of 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 literature focused on direct impacts of conflict, sometimes on long-term outcomes such as human capital rather than production. 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 need to be considered. Constructing a panel of VCs provides an expedient way to obtain an estimate of indirect effects in a way that avoids selection issues based on the assumption that all changes over time not explicitly controlled for can be directly or indirectly attributed to the conflict. While this implies our estimate is an upper bound, it provides a basis for further scrutiny or disaggregation, ideally complemented by a more structural approach towards identifying channels through which such effects materialize.

Finally, while much of existing analyses are ex post, often involving significant time lags, use of proxies such as NDVI at a high level of granularity allows our estimates to be used as a basis for measures (e.g., cash or in-kind transfers or opening up of markets) to help attenuate immediate conflict effects and in doing

so improve resilience and prevent longer-term erosion of productive capacity. Beyond informing design of such measures, the data presented here can potentially also be useful to assess their impact.

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

A large literature identified weather or price shocks that affect households' relative endowments as potential triggers for violent conflict by a large body of literature (see 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 to limit the transferability of substantive insights and require a different analytical approach.[1]

One advantage of agriculture is that remotely sensed covers large areas consistently. Satellite imagery is now routinely used to consistently quantify changes in land use such as deforestation (Hansen *et al.* 2013) or crop expansion (Potapov *et al.* 2022) globally. In the US, a Landsat-based crop data layer is available since the 1980s to allow parcel-level analysis (Lark *et al.* 2017). For developing countries, the use of such 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 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.[2] 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

[1] 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).
[2] Wouters *et al.* (2021) similarly use UAV imagery in Malawi to assess flood-related damage to houses.

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 rathe r 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 2019-22 time span 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 using 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

$$Y_{vt} = \alpha_v + \beta CI_{vt} + \boldsymbol{\gamma} X_{vt} + \lambda_t + \varepsilon_{vt} \quad (1)$$

where Y_{vt} is the outcome variable of interest in village v at year t; CI_{vt} is a an indicator for presence 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 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;[3] α_v is a village fixed effects that controls for time invariant factors such as agronomic suitability, access to infrastructure and economic opportunities, and local leadership quality; λ_ts are time fixed effects; and ε_{vt} is random error term.

Two coefficients in (1) are of particular interest: β measures the direct impact of conflict-related activities in affected villages while λ_{2022} captures the deviation of 2022 from the common trend. To the extent that time invariant (access to infrastructure, soil quality, village leadership) and time variant (weather) variables are controlled for, this can be interpreted as an estimate of indirect conflict effects. Interpreting the time dummy in this way assumes there are no other relevant time-varying variables that would need to be controlled for; if such variables exist, they can be included in the regressions or otherwise adjusted for. 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 in practice, we estimate the impact of conflict on two outcome variables. To cover the extensive margin, we assess the impact of conflict on area growing with

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

winter crops as of May 1. As decisions on planting of winter crops were made before the conflict started, we would expect to see effects only through either destruction of a field's crop cover or a failure to manage crops that had already been planted, expecting us to expect this effect to be relatively modest.

Conflict-related damages to fields or input shortages or price expectations may affect the ability to manage crops properly, thus leading to reductions in expected yield. To assess such effects for fields that, based on our crop classification are planted with winter cereal,[4] we use the NDVI, computed on the GEE platform, as a proxy for crop conditions and expected yield. This is motivated by the fact that recent 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 weather data (Aula *et al.* 2021), provides rather accurate yield prediction. An early application to the US and Ukraine is Becker-Reshef *et al.* (2010).[5]

We can use the parameters obtained by some of these studies to illustrate the order of magnitude of expected yield effects: For data from the 2012-16 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 t/ha or by 25%-50% with R^2 of between 0.5 and 0.85. For Argentina, Lopresti *et al.* (2015) find an increase of yield of 109 kg/ha with each additional point of peak NDVI as measured by MODIS data (R^2 of 0.53). For10 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 the highest 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 t/ha (from a mean of about 2.2 t/ha).

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 2000s, when some 7 mn. land owners were provided with land shares of about 4 ha each, the agricultural sector's value added doubled. Some 20 mn. ha of Ukraine's agricultural land is farmed by large farms, often with links to foreign capital (Deininger *et al.* 2018); 12 mn. ha is cultivated by small and household farms; and some 9.2 mn. ha was originally under state or communal land, a sector the size of which has been reduced significantly via disposal of land. was in non-transparent ways.

The war 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,[6]

[4] As wheat accounts for more than 90% of winter cereals, we use winter wheat and winter cereals interchangeably.
[5] 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 although Panek and Gozdowski (2020) obtain the best fit with NDVI values from a slightly earlier date.
[6] 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.

strengthen decentralization and transparency by allowing local 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 2000s and that depressed investment and productivity in the sector (Nivyievskyi *et al.* 2021).[7] Between July 1, 2021 when the moratorium was lifted and the start of the war when land markets were suspended,[8] some 0.25 mn. ha of agricultural land was transferred by sale or purchase.

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 mn. ton (t) of maize and wheat from the 2021 crop were still in storage when the war started, the 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, direct destruction of land and crops through war-related actions (bombs, land mines, or movement of heavy vehicles) directly reduces the productive potential of agricultural land. Finally, shortages of fuel, inputs such as seed, fertilizer, and pesticides, or labor make it difficult to properly manage winter crops or plant summer crops and will likely be associated with reduced output with small likely to be particularly affected. Taken together, these have a large impact: Aggregate assessments put aggregate direct damages in agriculture at US$ 4.29 billion (Neyter *et al.* 2022b)[9] and estimate indirect war-induced losses in 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).[10] Our methodology 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 comparisons of cloudless Sentinel-2 and Planet satellite imagery in bi-weekly intervals to identify conflict-related damages to specific fields in the 9 oblasts (districts) directly affected by military action.[11] Appendix figure 1 provides an example of the front line and damaged fields

[7] Zadorozhna (2020) also 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.
[8] Three laws to govern land relations under martial law (laws 2247-IX; 2254-IX, and 2255-IX were passed on May 12.
[9] 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.
[10] 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).
[11] These oblasts are Kyivska, Chernigivska, Sumska, Kharkivska, Luganska, Donetska, Zaporizka, Khersonska, and Mykolaivska.

for the June 6-19, 2022 period. The appendix also includes examples of 'before-after' images to illustrate 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 is clearly visible. For each VC and any of the two-week periods after Feb. 24, 2022, we define an indicator variable for whether or not 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, i.e., the 8-week period from Feb. 24 to April 24 values from which are used in regressions for winter crop area and a second 8-week period from April 25 to June 18 (together with values from Feb. 24) is included as a right-hand side variable 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).

Over time, the largest extent of damages was experienced 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 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 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.[12] 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 following standard guidelines (Waldner *et al.* 2019) was undertaken yearly from 2019-2021. In each year, two extended field trips, one for the winter and one for summer crops, were conducted (see figure 1 for route maps in each year). While conflict conditions

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

prevented *in situ* data collection during the spring, a ground survey for the 2022 crop could eventually be organized in June 2022 and is still ongoing at the time of writing.

All optical data from Sentinel-2 and SAR data from Sentinel-1 during the vegetation period was then used to generate crop classification map using a convoluted neural network on the Amazon Web Services cloud computing platform (Kussul *et al.* 2017; Shelestov *et al.* 2020) as well as a random forests classifier on the Google Earth Engine (GEE) platform (Shelestov *et al.* 2017).[13] For classifier training, half of the data was randomly assigned to training and independent validation samples and accuracies calculated based on independent validation dataset for each of the crops received (Kussul et al. 2018). For 2022, Sentinel-2 data was used to create a winter crop mask for the 2022 cropping season by computing the maximum value of vegetation index NDVI for the entire territory of Ukraine from Feb. 1 to May 31 on GEE and applying a threshold segmentation for winter crop mask creation.[14]

Table 2 shows the number of training samples for winter and summer crops collected each year as well as the F1 scores for winter crop classification maps which exceeds 95% in each of the years. Maps of the estimated winter crop area by VC generated on this basis as displayed in figure 2 illustrate a concentration of winter crops in the country's South and East and suggest a much lower level of winter crop 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 mn ha, area cultivated with winter crops in 2022 is indeed 11% below the 2019-21 average but well above the 7.5 mn. 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) who attribute most of the changes to differences in weather, highlighting the importance of controlling for such factors before attributing changes over time to conflict.[15]

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. Results from doing so, reported in panel B of table 2 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

[13] See Kussul *et. al* (2016 and 2017) for a detailed description of methodology for crop mapping based on satellite data. As the classification map based on a deep learning model on AWS is more accurate at small fields, it is used below.
[14] Threshold segmentation was based on maximum NDVI values and to separate winter cereal and rapeseed, an additional band index was calculated to detect the characteristic yellow flowering of winter rapeseed (d'Andrimont *et al.* 2020).
[15] 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.

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,[16] we use the crop masks obtained from the above land cover analysis for 2019-22, respectively, to compute NDVI on all fields planted to winter wheat for each of the 10-day periods ending on May11, 21, 31, and June 11 and aggregate these values at village level. Calculations were performed on the Google Earth Engine cloud computing platform.[17] Figure 3 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. Tabulating VC-level figures in panel C of table 2 confirms that NDVI in 2022 was uniformly lower than in earlier years.

3.3 Weather conditions

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 hours. For the 2019-22 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 cumulated GDD>0 days computed based on daily values of T_{min} and T_{max} in figure 4 illustrates a marked seasonal pattern and clear differences across years.[18] 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 figure 5 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. By contrast, in the 2021 season, ample spring and subsequent rainfall provided favorable growing conditions, contributing to what was widely considered a record harvest. Fall precipitation (i.e., until Dec. 1) was even lower in 2022 than in 2020 and, by end May, had approached levels of total rainfall similar to those observed in 2020.

[16] 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>0

[17] 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.

[18] In line with the empirical pattern, we define fall as the period between Oct 1 and Dec 1; winter as the period between Dec. 1 and Mar. 1; and spring as the period thereafter.

3.4 Farm structure

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 by the Ukraine State Statistics Service' reporting 'Form 29' to compute, for every rayon, the share of crop area by farm enterprises that cultivate between 500-2,500 ha or more than 2,500 ha nationally, i.e., either in the rayon or in other parts of the country. Results in table 4 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

Table 5 summarizes results from estimating equation (1) with detailed results in appendix table 1. 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.[19] 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 4 periods is estimated to reduce cultivated area by some 95 ha, in addition to a highly significant point estimate (of -0.10, see col. 6) for crop area directly damage. 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 an independent economy-wide effect of the war that may be due to manpower shortages, the difficulty of accessing purchased inputs, especially fuel, or an expectation of not being able to go to market when the crop will be harvested. The estimated area reduction of 82.1 ha per VC (col. 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.

[19] 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.

Finally, as appendix table 1 illustrates, the coefficients on weather-related variables and their squares can be given a plausible interpretation: GDD>0 and, precipitation variables (except rain in the fall) are positive and highly significant, though they exhibit decreasing marginal returns. The positive and quantitatively large coefficient on the number of dry days in fall is very large - an additional dry day is estimated to increase winter crop area by 58 ha or about 7% of the village average winter crop area.[20] 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 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.[21] Table 6 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 (col. 2) and the 1,862 VCs affected (col. 3) by conflict with the latter again subdivided into 1,485 VCs where no direct crop damage from conflict was sustained and 377 where such damage was incurred. Total predicted winter crop area is 8.4 mn. ha, 5.7 mn. ha in VCs unaffected by direct conflict and 2.7 mn ha in VCs affected by conflict (2 mn ha in VCs without and 0.7 mn ha in VCs with fields being damaged directly by conflict related activity).

As lines 2 and 4 illustrate, scenario one, i.e., hypothetical elimination of direct conflict, will change winter crop area only in VCs not directly affected by conflict, with a predicted increase in area of 102,255 ha (70,190 ha in VCs without and 32,064 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 623,670 ha, most (508,977 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 of 725,925 ha, 86% (or 623,670 ha) can be attributed to macro-effects and 14% to direct war-induced damages. With an average yield of 4 t/ha, this would translate into a loss of winter crop output of 2.9 mn t though ideally some 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 on 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 more than 90% 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.

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

[21] In terms of the model results reported in table 3 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.

Table 7 reports summary estimates from estimating equation (1) with (peak) NDVI on winter wheat fields as dependent variable with panel A is identical to table 5 and panel B adds farm size interactions.[22] In the preferred specification (column 6) all coefficients of interest are significant at 1% (panel A) and interactions at 5% (panel B). With a 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 unbiases estimates.

To translate regression coefficients into expected outcomes, note that a conservative reading of the literature suggests a 0.01 change in NDVI to translate into a yield change of some 112 kg. The point estimate (-0.002) 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 112 kg/ha. 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 213 kg/ha per ha of winter cereal in the VC. Noting that conflict-affected VCs cover about 1 mn. ha and have on average been exposed to conflict action for 4 of the 8 two-week periods, this implies a direct conflict-induced loss of up to 120,000 t of winter cereal.

Regarding indirect effects, we find a statistically highly significant year dummy, with a point estimate for the 2022 year dummy of -0.052.[23] Using the above parameters, this would translate into an upper bound for the indirect conflict-induced yield reduction of 582 kg/ha or close to 15%. With the 2022 winter wheat area at 7.274 mn ha, this would imply conflict-induced output losses of 4.2 mn t. Adding the 2.9 mn. t of lost output due to area reduction implies a total war-induced loss of winter cereal of 7.1 mn t or about 20% of the total.

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 0.81 t/ha (coefficient of 0.072) compared to 0.62 t/ha for medium sized and 0.45 t/ha for the largest group.

As an independent robustness check, we computed NDVI for the area covered by each year's winter crop 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

[22] See appendix tables 2 and 3 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 wheat NDVI and winter rain is insignificant.

[23] Coefficients also suggest that, after adjusting for weather effects NDVI in 2020 and 2021 was less (coefficient of -0.023) and more favorable (0.015) than in 2019 as the excluded category.

predictive power and (R^2 of 0.29 or 0.31) as would be expected if these lower resolution images convey less information.

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 25% with the importance of indirect effects vastly outweighing that of direct ones and small farmers being particularly affected.

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

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	Occupied	Fighting	present	indicator
P1: Feb 24 - Mar 12	0.009	268	0.04	0.08	0.12	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
Subtotal P1 - P4	0.037	498	0.122	0.104	0.177	0.184
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 (col. 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 (col. 3-5)

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

Year	Total sample size	Extent of training sample for collected			F1
		Winter cereal	Winger 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 Results for 2022 are preliminary as field data collection is still ongoing. The F1 score is TP/(TP+0.5*(FP+FN)).

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

		2019	2020	2021	2019-21	2022	Difference 2019-22 absolute	Difference 2019-22 %	No. VCs
Panel A: National winter crop area (mn. 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 wheat									
$NDVI_{ww}$ 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 wheat in the crop cover analysis for the year in question.
Source: Own computation from crop maps for winter crop area and sentinel imagery 2019-22.

Table 4: 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 SSSU form29.

Table 5: 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^2	0.095	0.095	0.095	0.095	0.095	0.096

Note: Results are from 2019-2022 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' (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 1 for full specification including weather variables. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010.

Table 6: Predicted direct and indirect effects of conflict on winter crop area in ha

	Total	Village councils with conflict activity?			
		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
(2) No conflict (S1)	8,485,308	5,728,333	2,756,975	2,066,638	690,337
(3) No macro & conflict (S2)	9,108,978	6,237,310	2,871,668	2,158,110	713,559
(4) Net conflict effect (S1-B)	102,255	-	102,255	70,190	32,064
(5) Net macro effect (S2-S1)	623,670	508,977	114,693	91,472	23,222
(6) Conflict & macro effect (S2-B)	725,925	508,977	216,948	161,662	55,286
No. of VCs	10,125	8,263	1,862	1,485	377

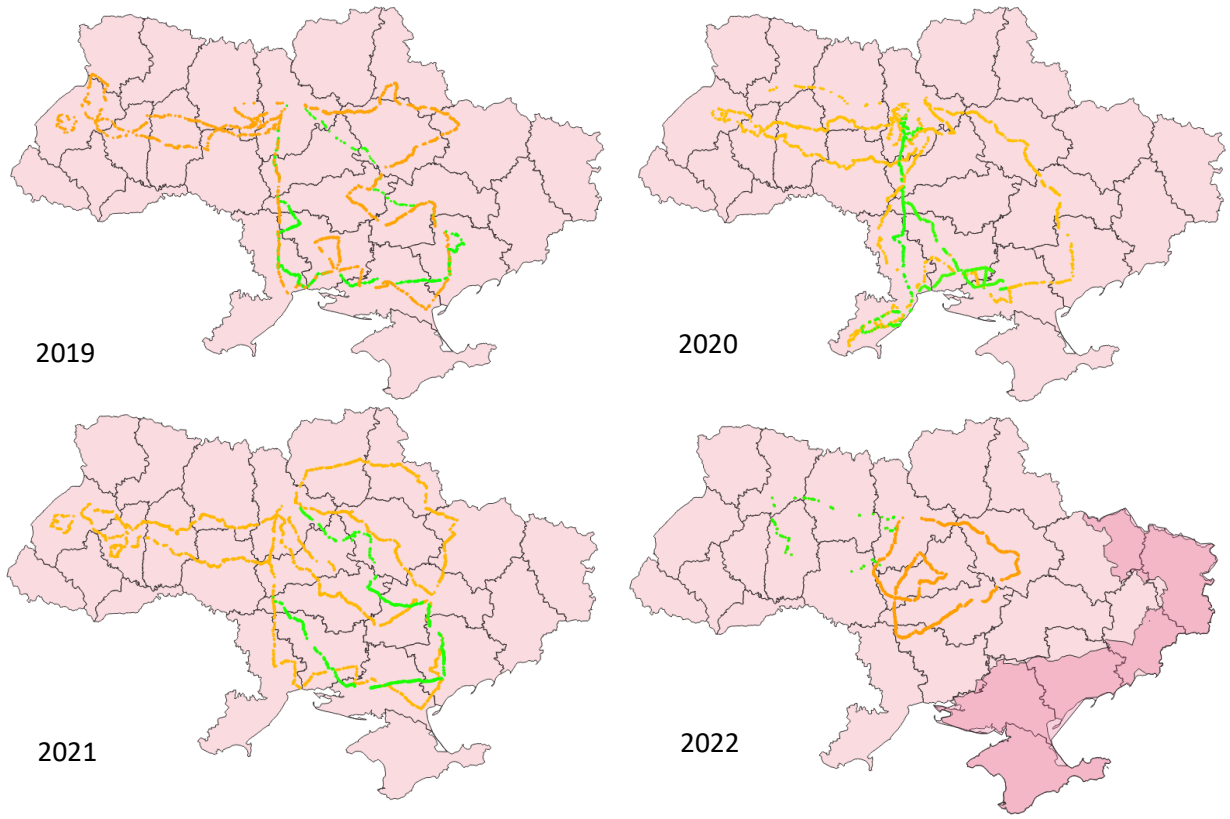
Source: Own computation based on coefficients from table 4 column 6.

Table 7: 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		-0.005*	-0.000	0.000	0.000	-0.019***
		(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Crop damage area (100 ha)	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year 2020	-0.023***	-0.023***	-0.023***	-0.023***	-0.023***	-0.023***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Year 2021	0.015***	0.014***	0.015***	0.015***	0.015***	0.013***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Year 2022	-0.054***	-0.054***	-0.054***	-0.054***	-0.054***	-0.052***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
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		-0.005**	0.001	0.000	-0.000	-0.019***
		(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
Damaged area (100 ha)	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year 2020	-0.025***	-0.025***	-0.024***	-0.025***	-0.025***	-0.025***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Year 2021	0.015***	0.014***	0.015***	0.015***	0.015***	0.013***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Year 2022	-0.072***	-0.072***	-0.072***	-0.072***	-0.072***	-0.072***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Yr 2022 # % >2500 ha	0.030***	0.030***	0.029***	0.029***	0.030***	0.032***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Yr 2022 # % 500-2500ha	0.013*	0.014**	0.013*	0.013*	0.013*	0.016**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
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

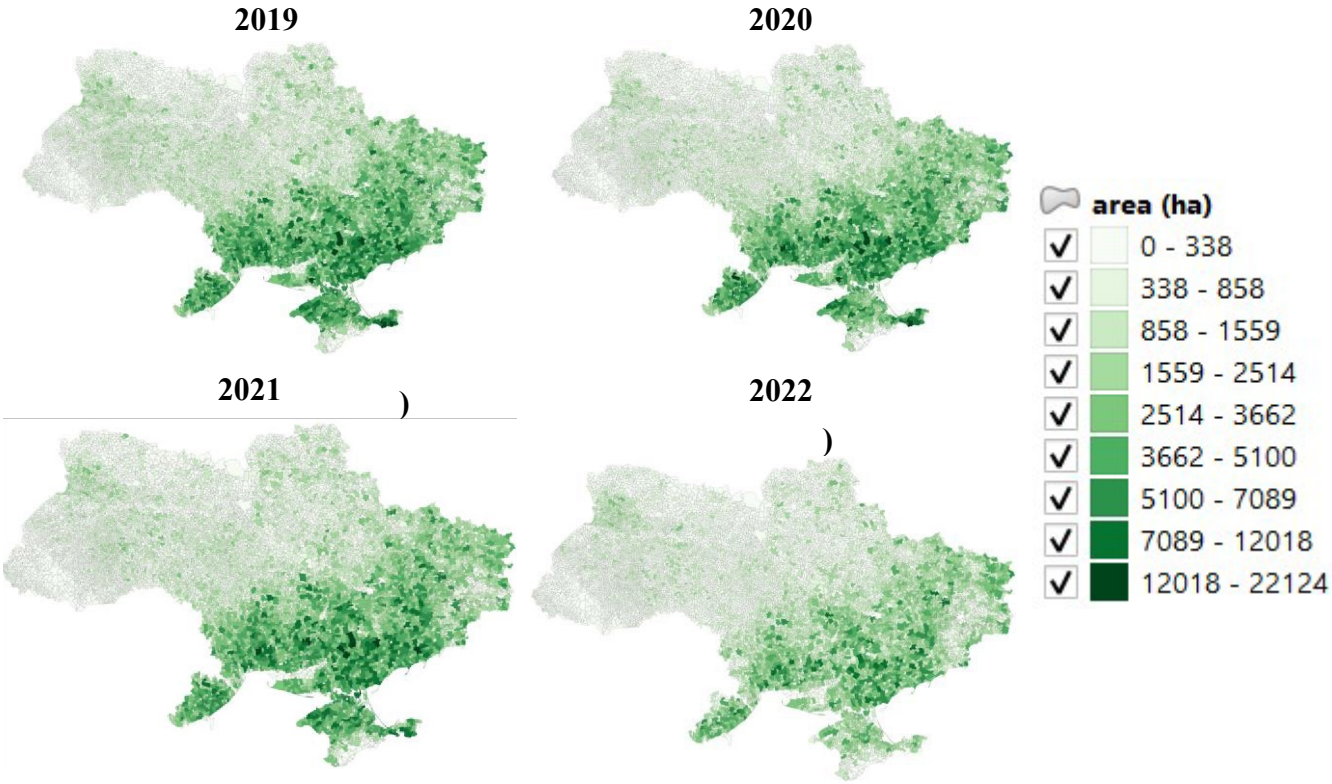
Note: Results are from panel regressions with VC fixed effects where the dependent variable is the NDVI for fields planted with winter wheat in each of the relevant years. Crimea and areas occupied since 2014 are excluded. 'Any' is the maximum over the 8 two-week periods considered whereas 'conflict 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 for tables with all weather-related variables. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010.

Figure 1: Routes for in-situ training data collection, 2019-2022



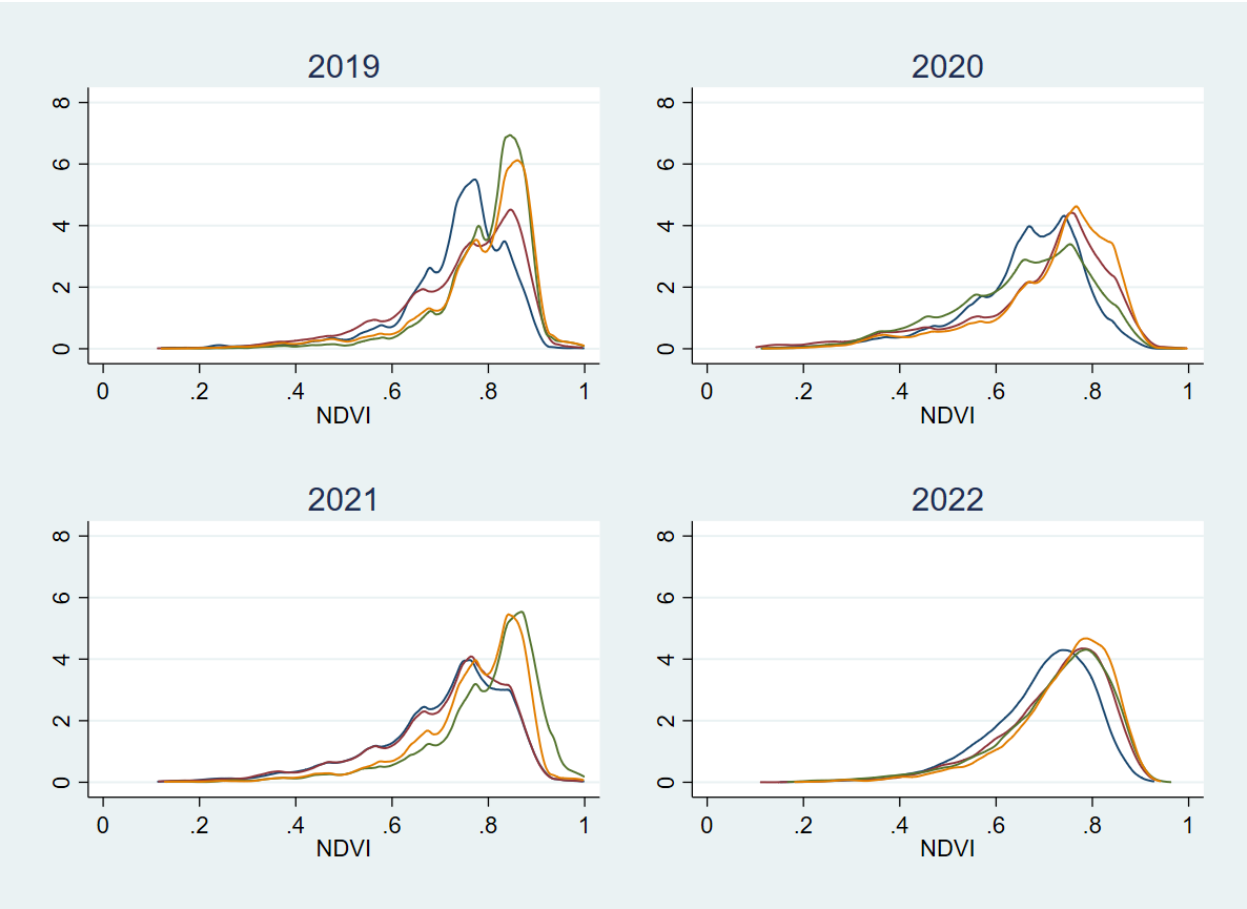
Note: Green and orange refer to the paths of ground data collection for winter and summer crops, respectively. For 2022, data collection is still ongoing and area in a darker shade of red is currently occupied by Russian forces.

Figure 2: Map of winter crop cover for 2019 to 2022 growing seasons



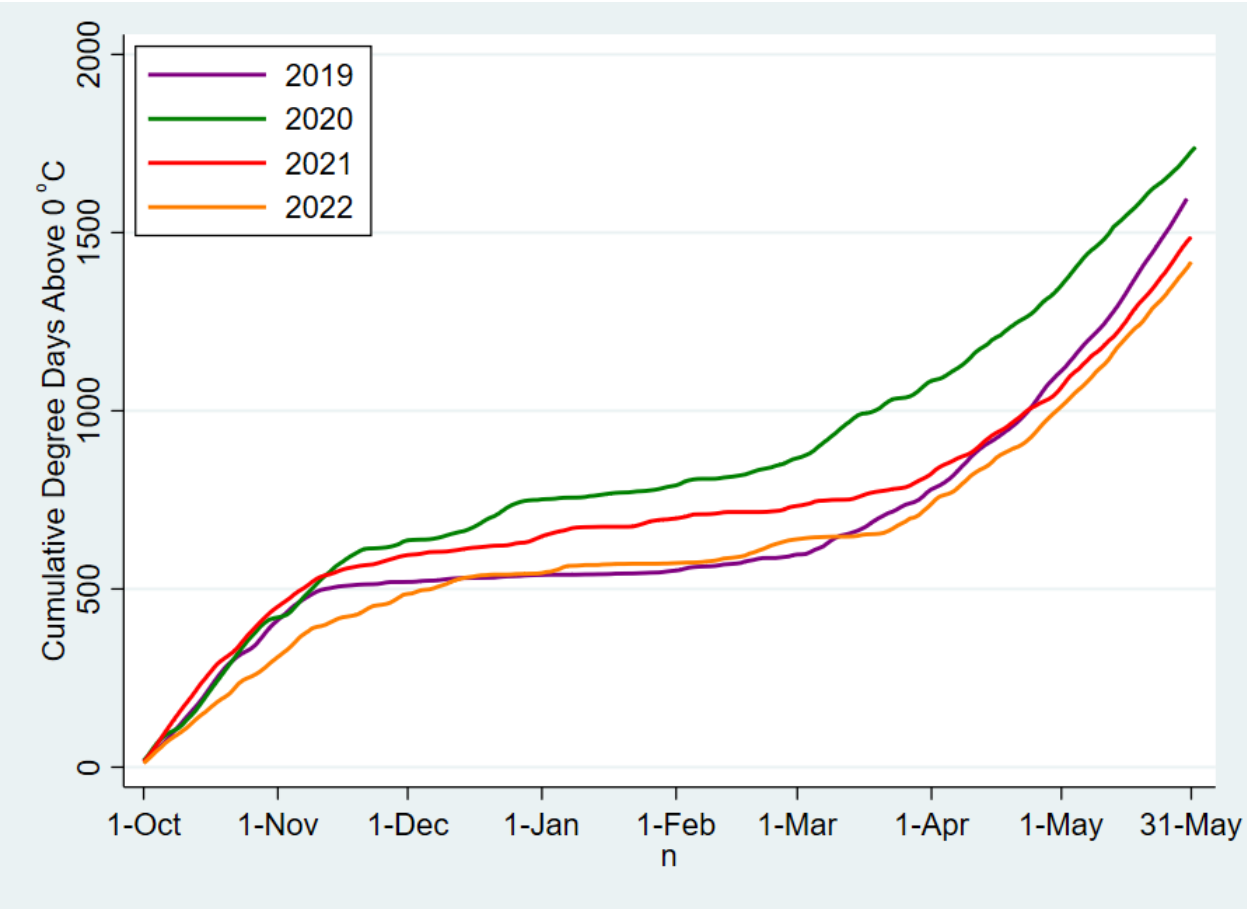
Source: Own computation using machine learning techniques as described in the text.

Figure 3: NDVI for fields grown with winter wheat for different time periods, 2019-22



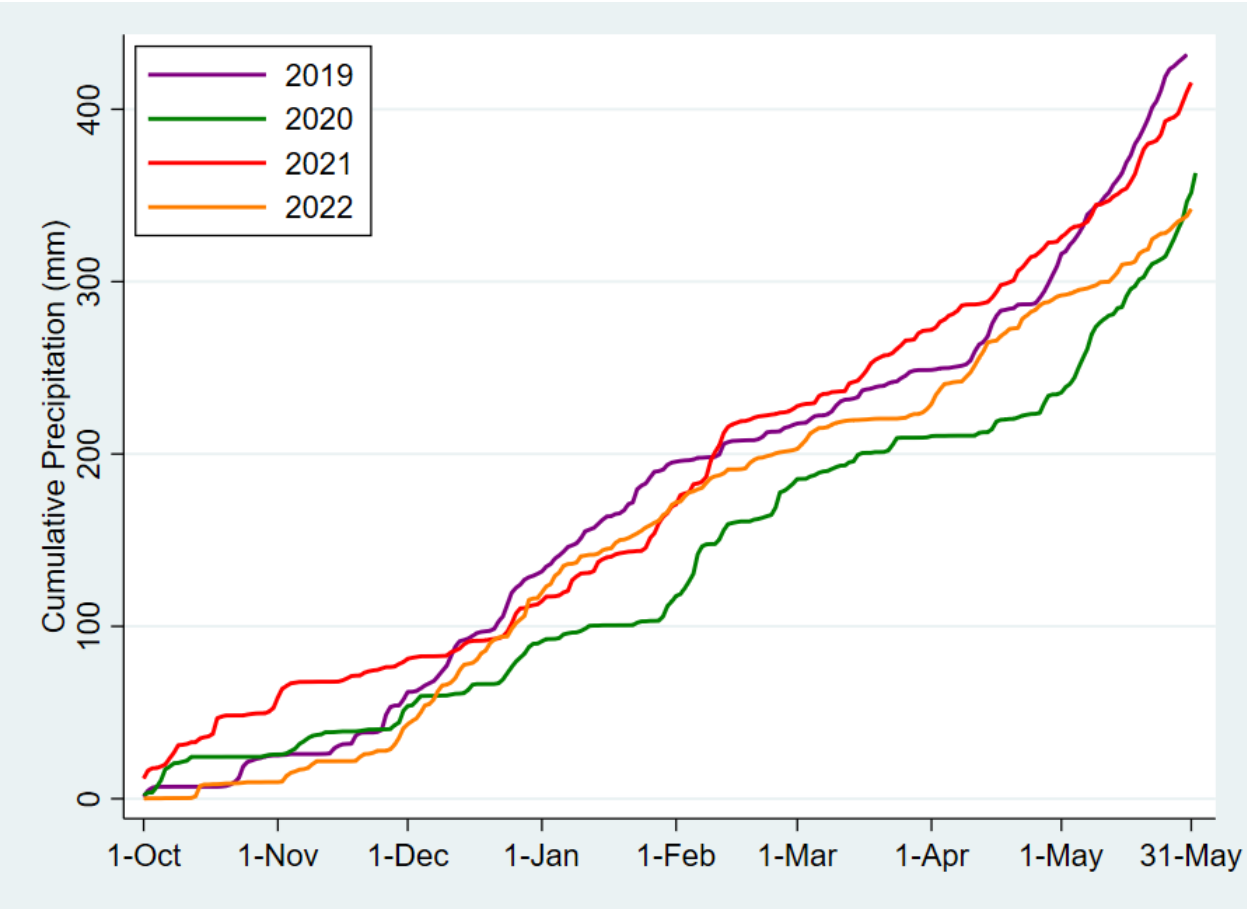
Note: Blue=May 1-11; Red=May12- 21; Green=May 22-31 Orange=June 1-11.
Source: Own analysis using GEE cloud computing platform.

Figure 4: Cumulative growing degree days (GDD) above 0ºC over October 1 – May 31 (winter crop growing season)



Source: Own computation from JRC GFS as described in the text.

Figure 5: Cumulative daily precipitation for the 2019-22 growing seasons (Oct 1 of previous to May 31 of relevant year)



Source: Own computation from JRC GFS as described in the text.

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APPENDIX TABLES AND FIGURES

Appendix table 1: 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>0 (Oct 1-Apr 30)	0.760***	0.792***	0.759***	0.808***	0.812***	0.897***
	(0.193)	(0.194)	(0.193)	(0.194)	(0.194)	(0.195)
GDD>0 squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation fall (mm)	0.084	0.108	0.080	0.187	0.192	0.140
	(0.404)	(0.405)	(0.405)	(0.405)	(0.405)	(0.404)
Precipitation winter (mm)	3.177***	3.239***	3.174***	3.306***	3.314***	3.342***
	(0.319)	(0.321)	(0.320)	(0.321)	(0.321)	(0.321)
Precipitation spring (mm)	2.310***	2.289***	2.311***	2.259***	2.257***	2.271***
	(0.421)	(0.421)	(0.421)	(0.421)	(0.421)	(0.421)
Precipitation fall squared	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Precipitation winter squared	-0.005***	-0.006***	-0.005***	-0.006***	-0.006***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Precipitation spring squared	-0.014***	-0.014***	-0.014***	-0.013***	-0.013***	-0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Zero rain days fall	59.101***	58.867***	59.101***	58.744***	58.701***	58.131***
	(3.802)	(3.804)	(3.802)	(3.802)	(3.802)	(3.805)
Zero rain days winter	1.796	2.103	1.779	2.550	2.632	2.579
	(1.684)	(1.693)	(1.690)	(1.698)	(1.699)	(1.690)
Zero rain days spring	-0.650	0.005	-0.681	0.825	0.953	1.201
	(3.031)	(3.055)	(3.042)	(3.061)	(3.062)	(3.052)
Zero rain days fall 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)
Zero rain days winter 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)
Zero rain days spring 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^2	0.095	0.095	0.095	0.095	0.095	0.096

Note: Results are from 2019-2022 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. 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 1 for full specification including weather variables. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010.

Appendix table 2: 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		-0.005*	-0.000	0.000	0.000	-0.019***
		(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Crop damage area (100 ha)	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDD>0 (Oct 1-May 31)	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDD>0 squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation fall (mm)	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation fall squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation winter (mm)	0.001***	0.001***	0.001***	0.001***	0.001***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation winter squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation spring (mm)	0.000**	0.000***	0.000**	0.000**	0.000**	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation spring squared	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Zero rain days fall	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Zero rain days winter	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Zero rain days spring	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Zero rain days fall squared	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Zero rain days winter squared	-0.000	-0.000	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Zero rain days spring squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year 2020	-0.023***	-0.023***	-0.023***	-0.023***	-0.023***	-0.023***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Year 2021	0.015***	0.014***	0.015***	0.015***	0.015***	0.013***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Year 2022	-0.054***	-0.054***	-0.054***	-0.054***	-0.054***	-0.052***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Constant	0.157***	0.155***	0.157***	0.157***	0.157***	0.141***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
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

Note: Results are from 2019-2022 panel regressions where the unit of observation is the village council and the dependent variable is the NDVI for fields planted with winter wheat in each of the relevant years. 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 1 for full specification including weather variables. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010.

Appendix table 3: 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		-0.005**	0.001	0.000	-0.000	-0.019***
		(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
Crop damage area (100 ha)	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDD>0 (Oct 1-May 31)	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDD>0 squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation fall (mm)	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation fall squared	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation winter (mm)	0.000**	0.000***	0.000**	0.000**	0.000**	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation winter squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation spring (mm)	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation spring squared	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Zero rain days fall	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Zero rain days winter	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Zero rain days spring	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Zero rain days fall squared	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Zero rain days winter squared	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Zero rain days spring squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year 2020	-0.025***	-0.025***	-0.024***	-0.025***	-0.025***	-0.025***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Year 2021	0.015***	0.014***	0.015***	0.015***	0.015***	0.013***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Year 2022	-0.072***	-0.072***	-0.072***	-0.072***	-0.072***	-0.072***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Year 2022 # share>2500ha	0.030***	0.030***	0.029***	0.029***	0.030***	0.032***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Year 2022#share>=500ha & <2500ha	0.013*	0.014**	0.013*	0.013*	0.013*	0.016**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Constant	0.133***	0.132***	0.133***	0.133***	0.133***	0.118***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
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 2019-2022 panel regressions where the unit of observation is the village council and the dependent variable is the NDVI for fields planted with winter wheat in each of the relevant years. 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 1 for full specification including weather variables. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010.

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Appendix table 4: Predicted direct and indirect effects of conflict on Landsat NDVI of winter cereal fields

		Conflict indicator				
	None	**Under occupation**	**Conflict actions**	**Troop presence**	**Any**	**Conflict intensity**
Conflict indicator		0.003	-0.008***	-0.003	-0.003	-0.006*
		(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
Area with crop damage (ha)	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDD>0 (Oct 1-Apr 30)	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDD>0 squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation fall (mm)	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation winter (mm)	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation spring (mm)	-0.001***	-0.001***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation fall squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation winter squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation spring squared	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Zero rain days fall	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Zero rain days winter	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Zero rain days spring	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Zero rain days fall squared	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Zero rain days winter squared	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Zero rain days spring squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year 2020	0.004	0.004	0.003	0.004	0.004	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Year 2021	0.012***	0.013***	0.011***	0.012***	0.012***	0.012***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Year 2022	-0.043***	-0.044***	-0.043***	-0.043***	-0.043***	-0.042***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Constant	0.111***	0.112***	0.113***	0.111***	0.111***	0.106***
	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)
No. of obs	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 2019-2022 panel regressions where the unit of observation is the village council and the dependent variable is the NDVI for fields planted with winter wheat in each of the relevant years. 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 1 for full specification including weather variables. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010.

Appendix table 5: Effects of conflict on Landsat NDVI and farm size on winter cereal fields

		Conflict indicator				
	None	**Under occupation**	**Conflict actions**	**Troop presence**	**Any**	**Conflict intensity**
Conflict indicator		0.002	-0.009***	-0.004	-0.005*	-0.007**
		(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
Crop damage area (100 ha)	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDD>0 (Oct 1-May 31)	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDD>0 squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation fall (mm)	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation fall 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)
Precipitation winter (mm)	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation winter squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation spring (mm)	-0.000*	-0.000*	-0.000*	-0.000*	-0.000*	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation spring squared	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Zero rain days fall	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Zero rain days fall squared	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Zero rain days winter	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Zero rain days winter squared	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Zero rain days spring	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Zero rain days spring squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year 2020	0.001	0.001	0.001	0.001	0.001	0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Year 2021	0.013***	0.013***	0.011***	0.012***	0.012***	0.012***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Year 2022	-0.075***	-0.075***	-0.075***	-0.075***	-0.075***	-0.075***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Year 2022 # share>2500ha	0.047***	0.047***	0.048***	0.048***	0.048***	0.048***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Year 2022 # share>=500ha & <2500ha	0.031***	0.031***	0.033***	0.032***	0.032***	0.032***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Constant	0.076**	0.077**	0.079**	0.076**	0.077**	0.070**
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
No. of obs	35,439	35,439	35,439	35,439	35,439	35,439
R-squared	0.312	0.312	0.312	0.312	0.312	0.312

Note: Results are from 2019-2022 panel regressions where the unit of observation is the village council and the dependent variable is the NDVI for fields planted with winter wheat in each of the relevant years. 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 1 for full specification including weather variables. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010.

Appendix table 6: Predicted direct and indirect effects of conflict on MODIS NDVI of winter cereal fields

		Conflict indicator				
	None	**Under occupation**	**Conflict actions**	**Troop presence**	**Any**	**Conflict intensity**
Conflict indicator		0.002	-0.001	0.005**	0.004**	-0.009***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Area with crop damage (ha)	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDD>0 (Oct 1-Apr 31)	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDD>0 squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation fall (mm)	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation winter (mm)	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation spring (mm)	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation fall squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation winter squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation spring squared	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Zero rain days fall	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Zero rain days fall	-0.000	-0.000	-0.000	-0.000*	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Zero rain days fall	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Zero rain days fall squared	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Zero rain days fall squared	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Zero rain days fall squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year 2020	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Year 2021	0.027***	0.028***	0.027***	0.028***	0.028***	0.026***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Year 2022	-0.020***	-0.020***	-0.020***	-0.021***	-0.021***	-0.019***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.129***	0.130***	0.129***	0.129***	0.128***	0.122***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
No. of obs	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

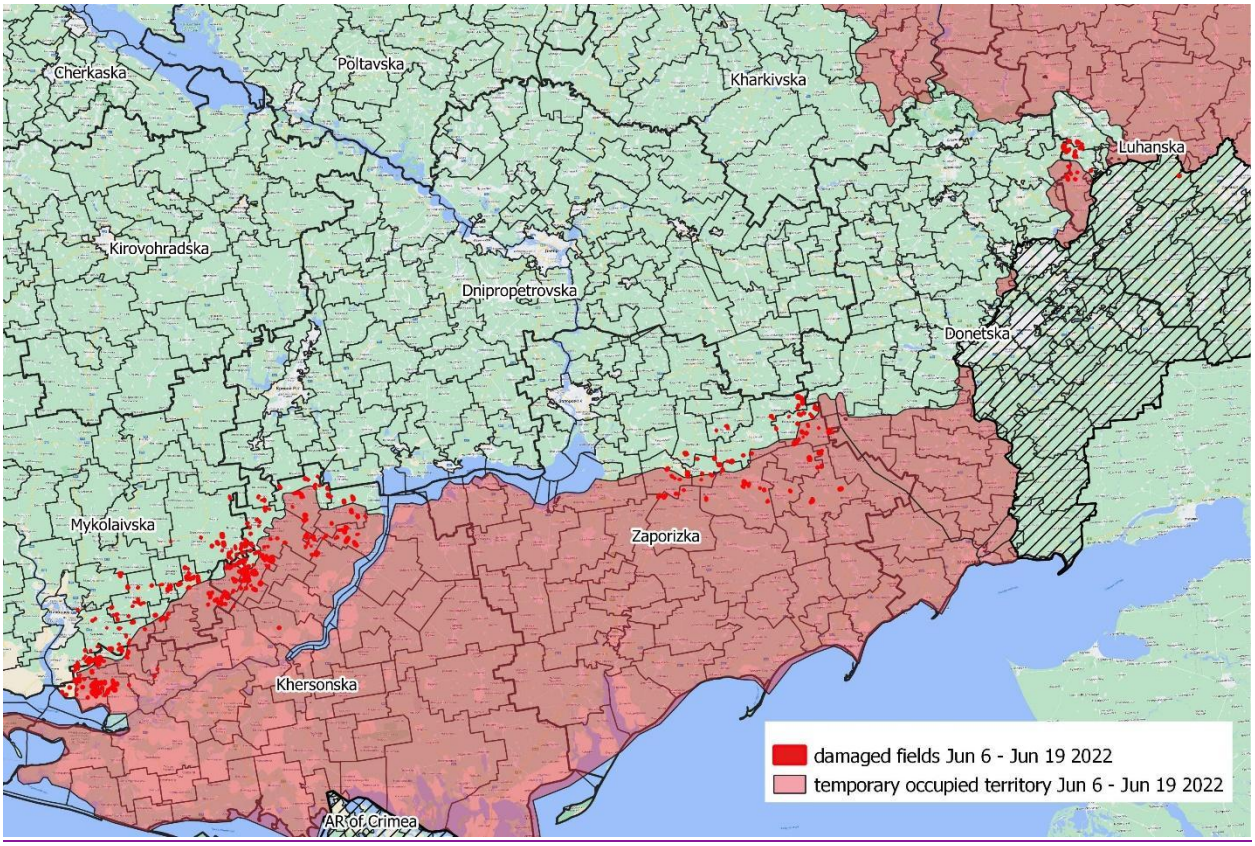
Note: Results are from 2019-2022 panel regressions where the unit of observation is the village council and the dependent variable is the NDVI for fields planted with winter wheat in each of the relevant years. Crimea and areas that have been occupied since 2014 are excluded. GDD is cumulative growing 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 1 for full specification including weather variables. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010.

Appendix table 7: Effects of conflict on MODIS NDVI and farm size on winter cereal fields

		Conflict indicator				
	None	**Under occupation**	**Conflict actions**	**Troop presence**	**Any**	**Conflict intensity**
Conflict indicator		0.003	0.001	0.006***	0.005***	-0.007***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Crop damage area (100 ha)	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDD>0 (Oct 1-May 31)	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDD>0 squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation fall (mm)	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation fall 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)
Precipitation winter (mm)	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation winter squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation spring (mm)	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation spring squared	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Zero rain days fall	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Zero rain days fall squared	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Zero rain days winter	0.004***	0.004***	0.004***	0.004***	0.004***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Zero rain days winter squared	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Zero rain days spring	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Zero rain days spring squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year 2020	-0.012***	-0.012***	-0.012***	-0.012***	-0.012***	-0.012***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Year 2021	0.028***	0.028***	0.028***	0.029***	0.029***	0.027***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Year 2022	-0.028***	-0.028***	-0.028***	-0.028***	-0.028***	-0.028***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Year 2022 # share>2500ha	0.015***	0.015***	0.015***	0.014***	0.014***	0.016***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Year 2022 # share>=500ha & <2500ha	0.006	0.005	0.006	0.004	0.004	0.007
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Constant	0.109***	0.110***	0.109***	0.109***	0.109***	0.103***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
No. of obs	36,724	36,724	36,724	36,724	36,724	36,724
R-squared	0.288	0.288	0.288	0.288	0.288	0.288

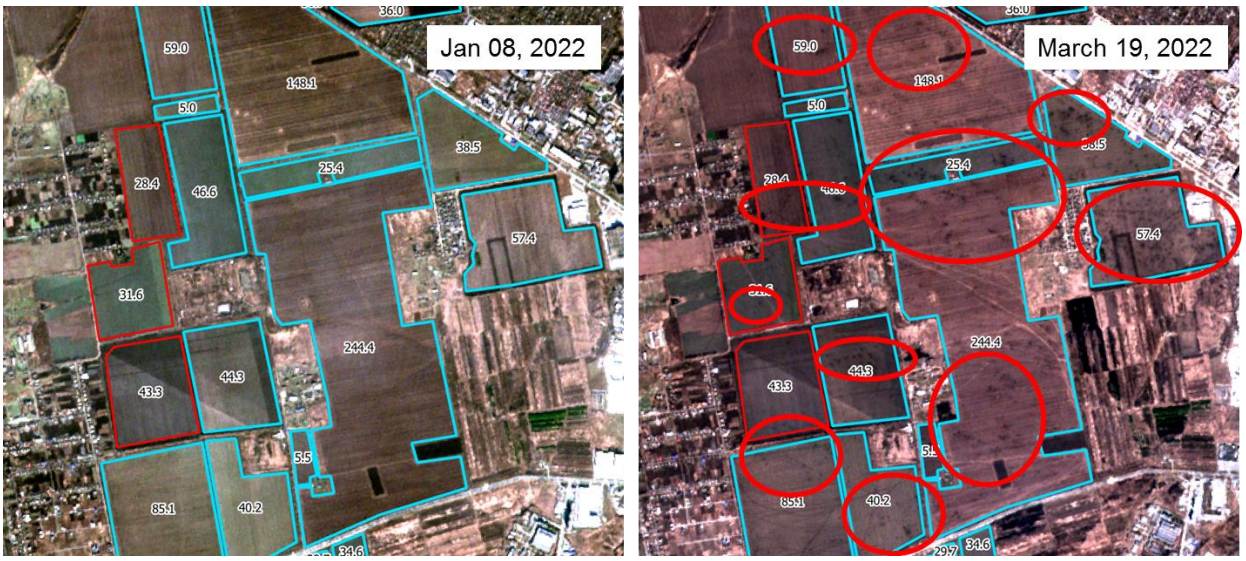
Note: Results are from 2019-2022 panel regressions where the unit of observation is the village council and the dependent variable is the NDVI for fields planted with winter wheat in each of the relevant years. Crimea and areas that have been occupied since 2014 are excluded. GDD is cumulative growing 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 1 for full specification including weather variables. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010.

Appendix figure 1: Example of location of fields damaged by fighting



Appendix figures: Examples of crop damage from sentinel2 satellite imagery

Damage of winter crops fields due to artillery fighting, Nizhynska OTG



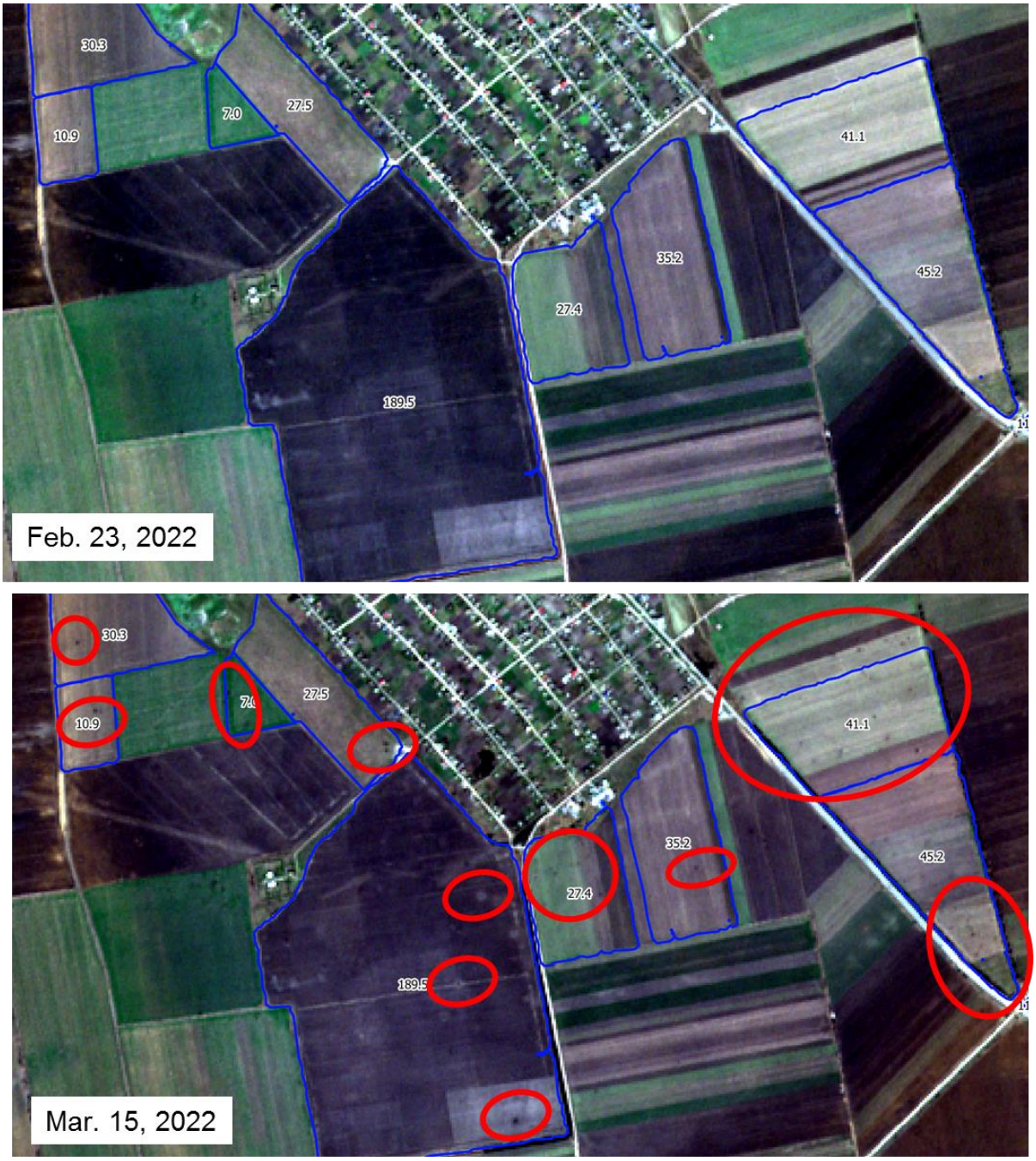
Damage of winter crops fields due to artillery fighting, Mariupolska OTG

Damage of fields (including winter crops) due to artillery fighting, Vugledarska OTG


ШЕПТУХИ
Белаши
Дергачевский полигон ТБО
дорожная
Google

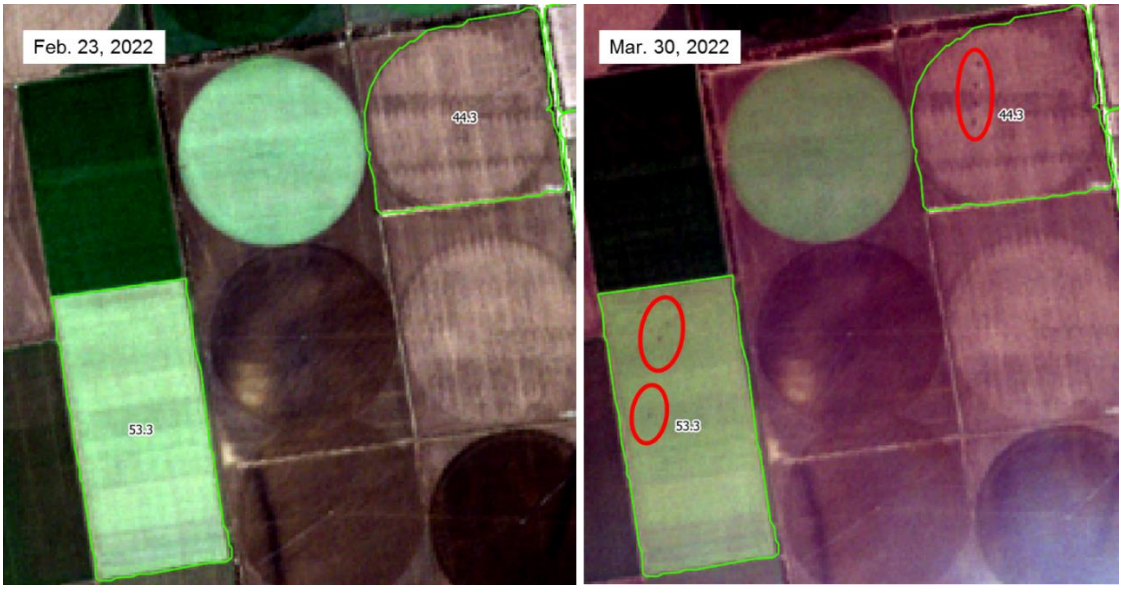

Mar 17, 2022

Damage of fields due to artillery fighting, Dergachivska OTG



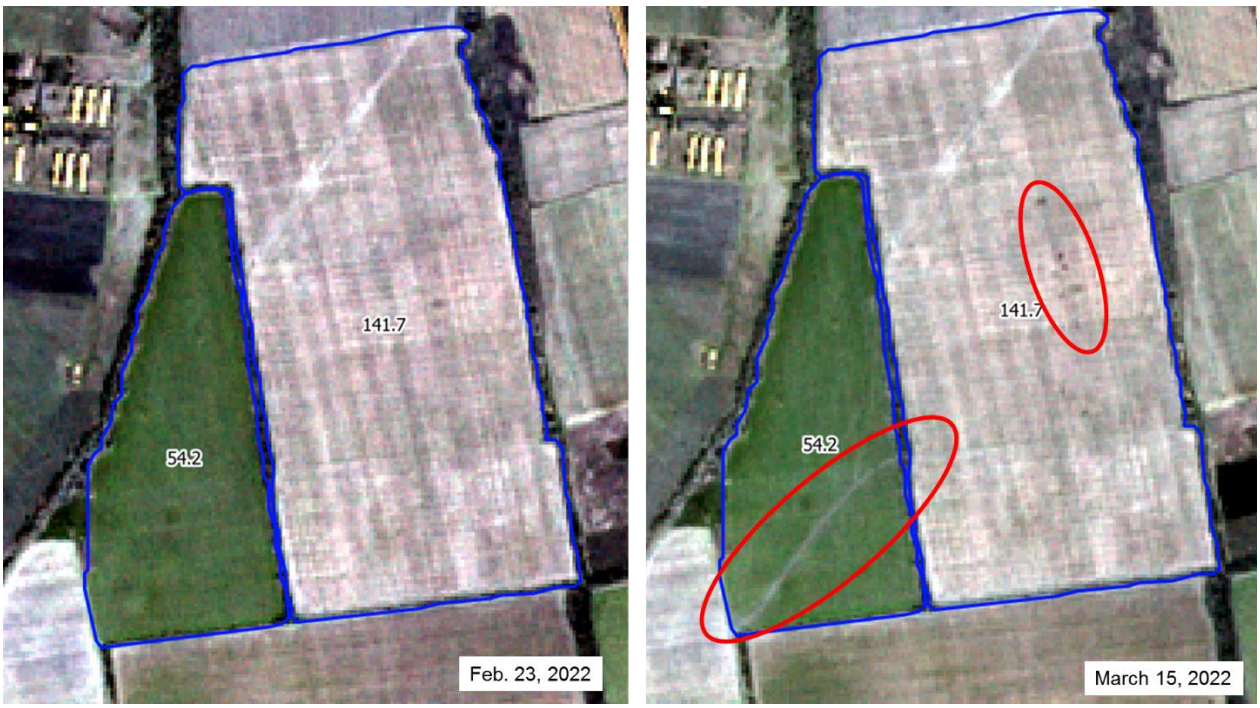
Damage of fields due to artillery fighting, Chernobaivkska OTG

Damage of fields due to artillery fighting, Novovorontsovska OTG

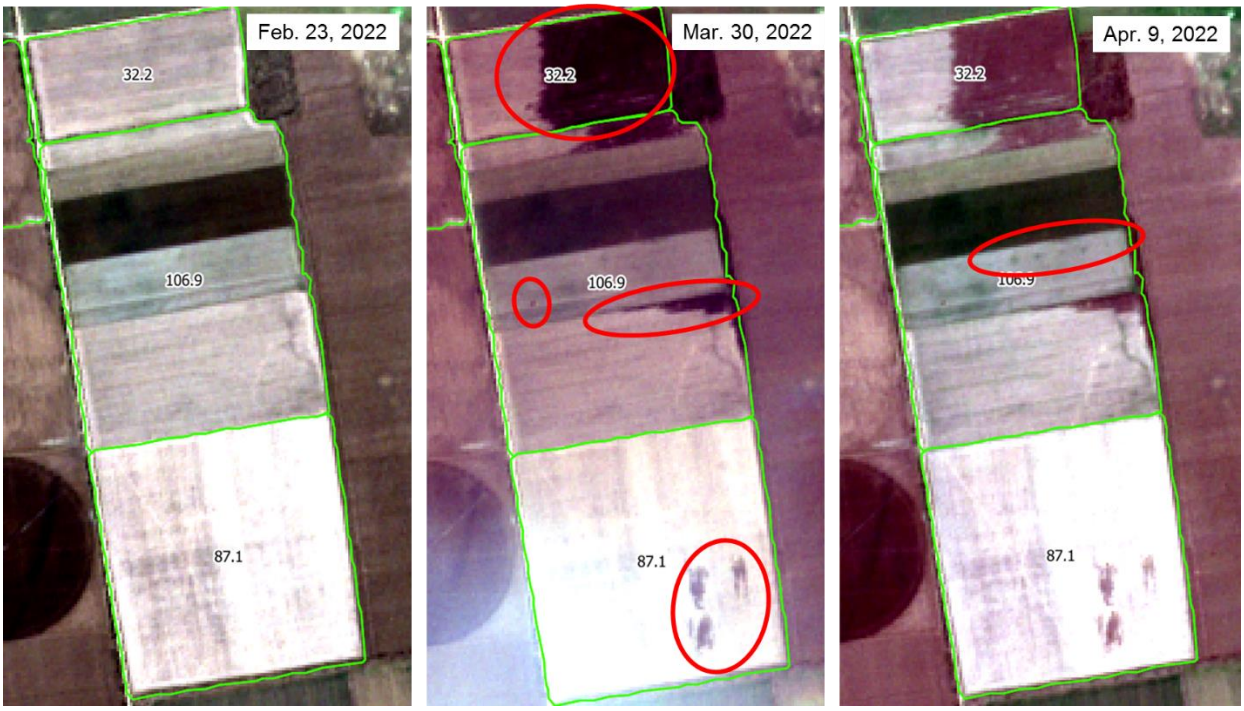


Damage of fields due to artillery fighting, Chernobaivkska OTG

Damage of fields due to artillery fighting, Vysokopilska OTG

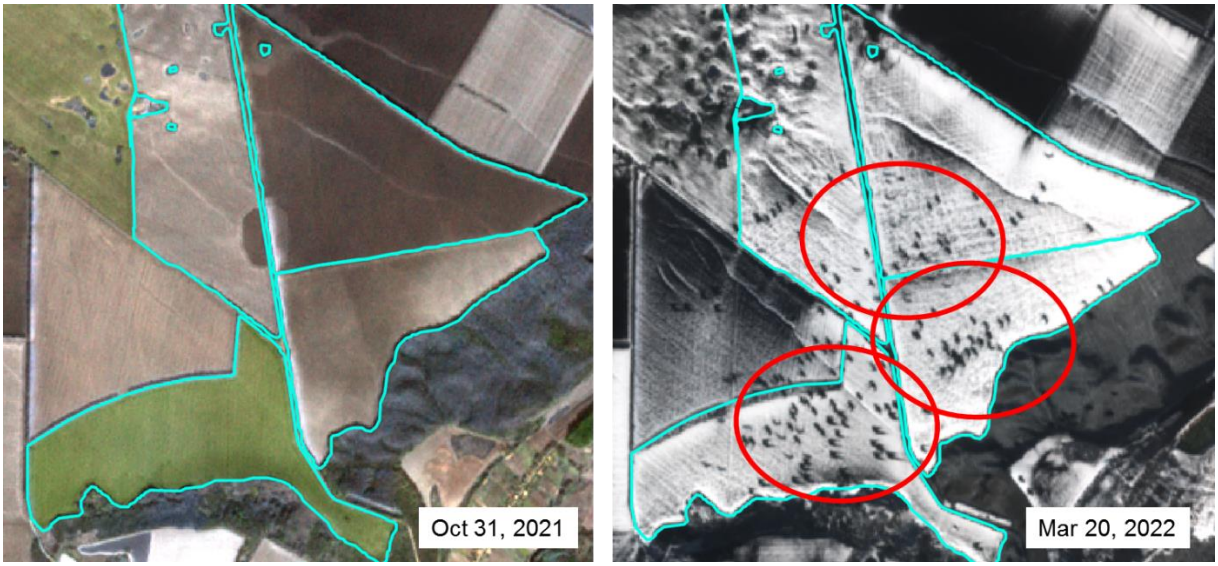


Damage to winter crop fields due to the movement of inappropriate equipment and due to artillery fighting, Khersonska OTG

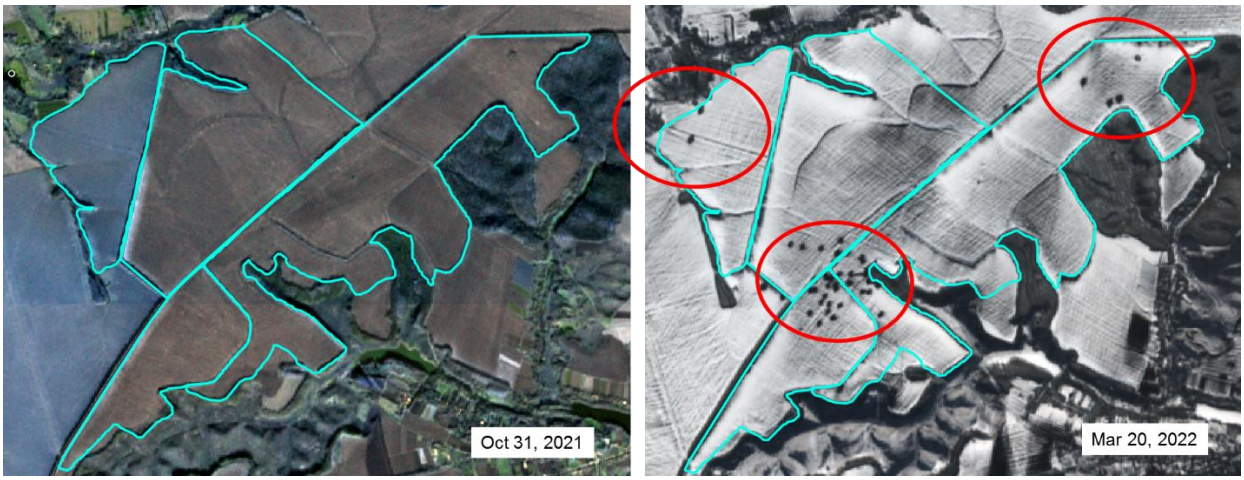


Damage of fields due to artillery fighting and stubble burning (may be caused by ordnance, aircrafts wreckage, etc.), Chernobaivkska OTG

Damage of fields due to stubble burning (may be caused by an artillery shell, rockets or aircrafts wreckage, etc.), Novoraiska OTG



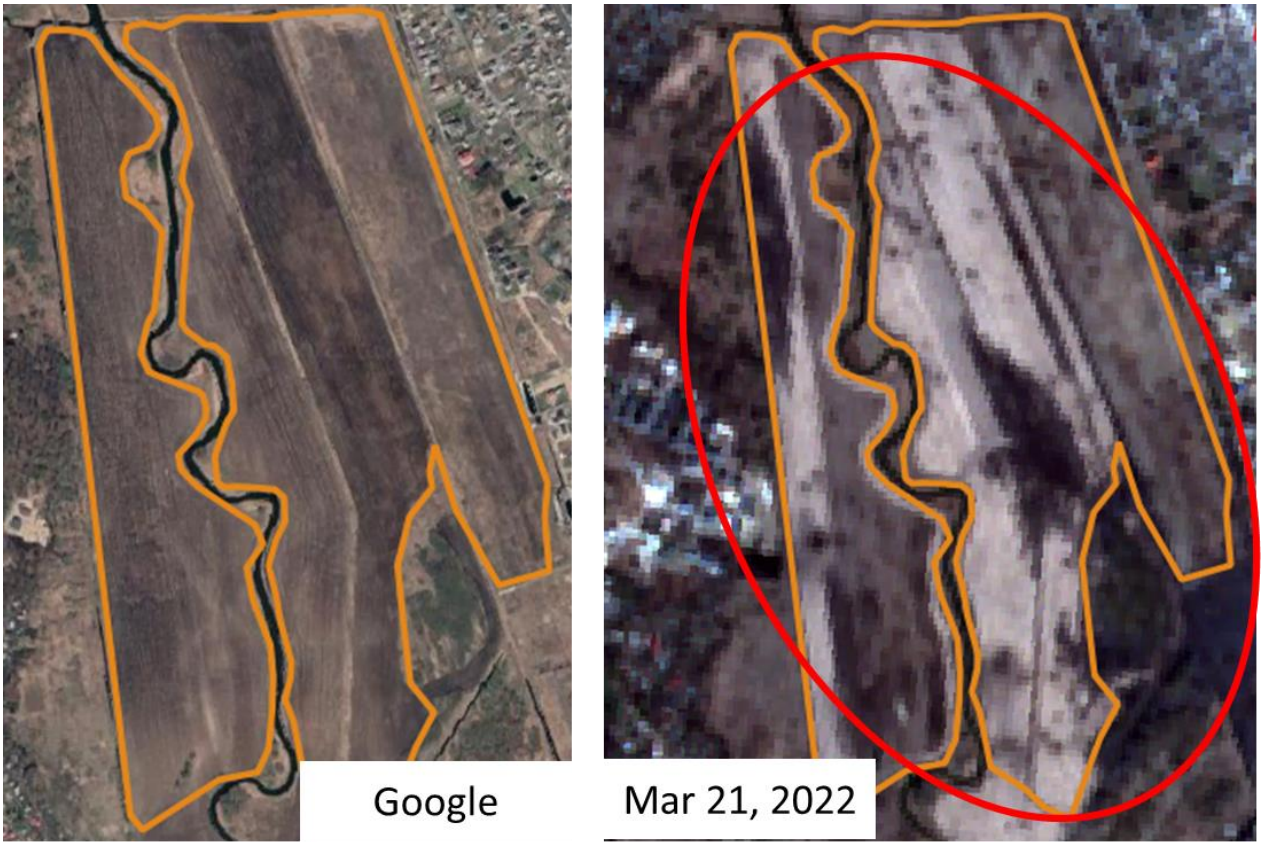
Damage of fields due to artillery fighting, Velykopysarivska OTG



Damage of fields due to artillery fighting, Trostyanetska OTG

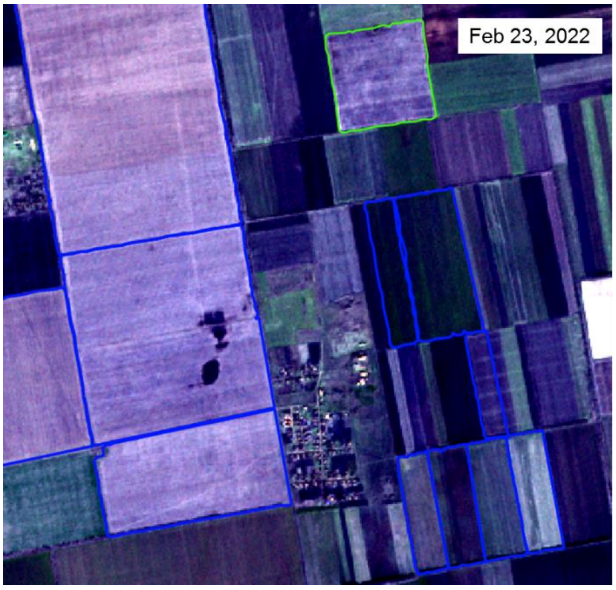
Damage of fields due to artillery fighting and to stubble burning (may be caused by an artillery shell, rockets or aircrafts wreckage, etc.), Chernobaivkska OTG

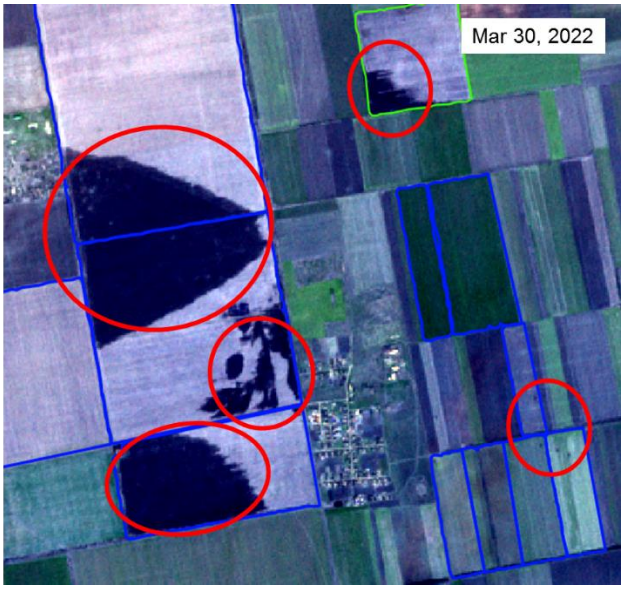
Damage of winter crops fields due to artillery fighting, Bucha OTG

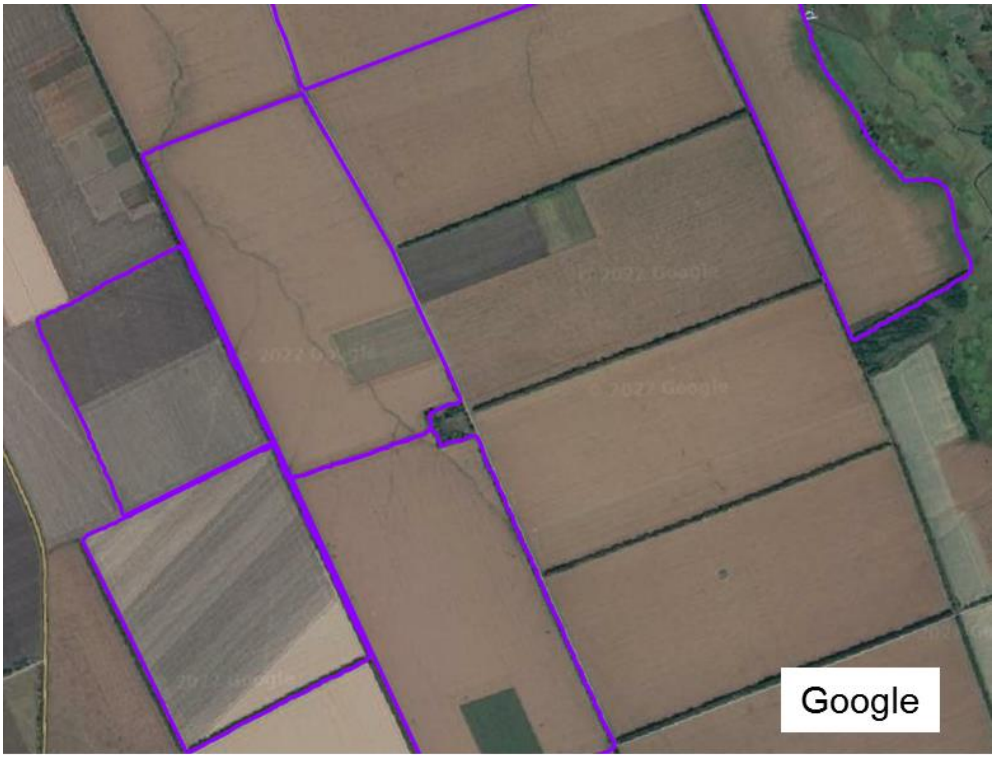


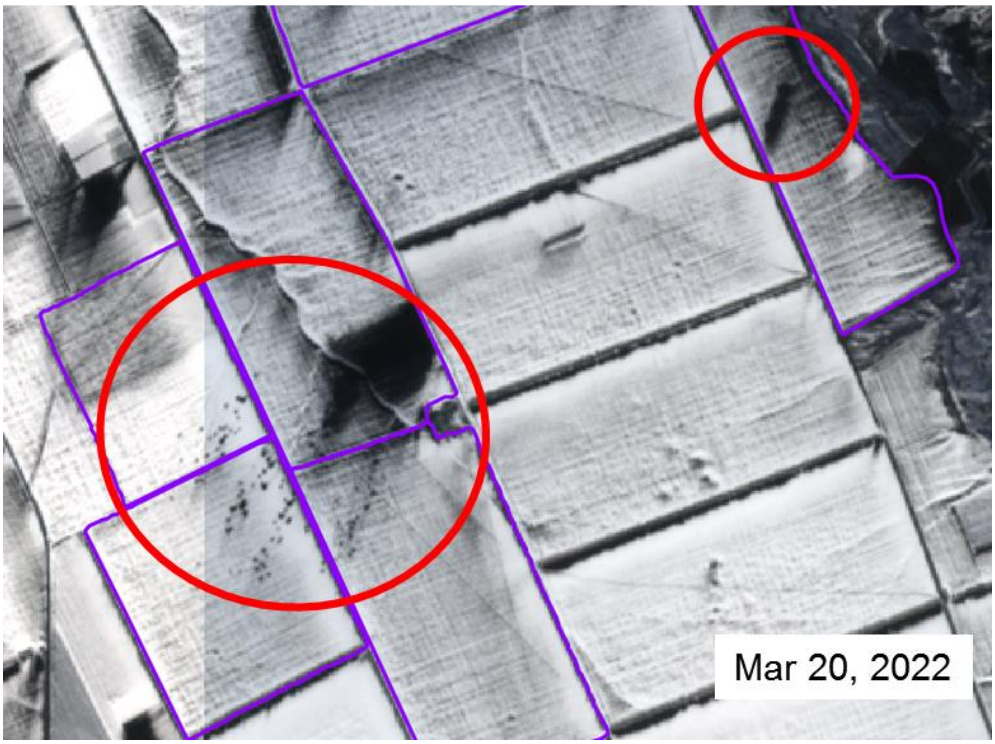
Damage of fields due to artillery fighting, burned area, Bucha OTG

Damage of fields due to artillery fighting, Shevchenkivska OTG



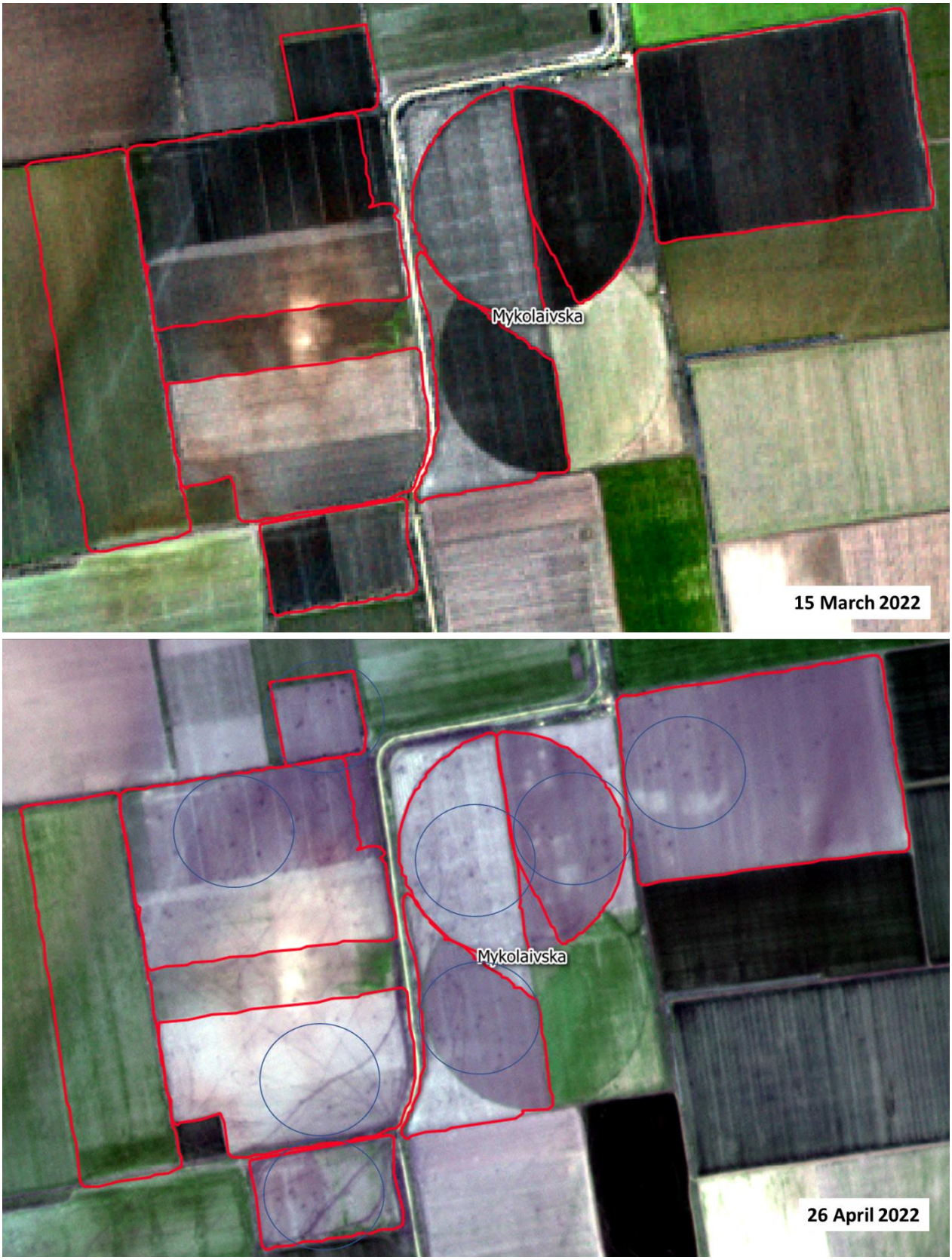




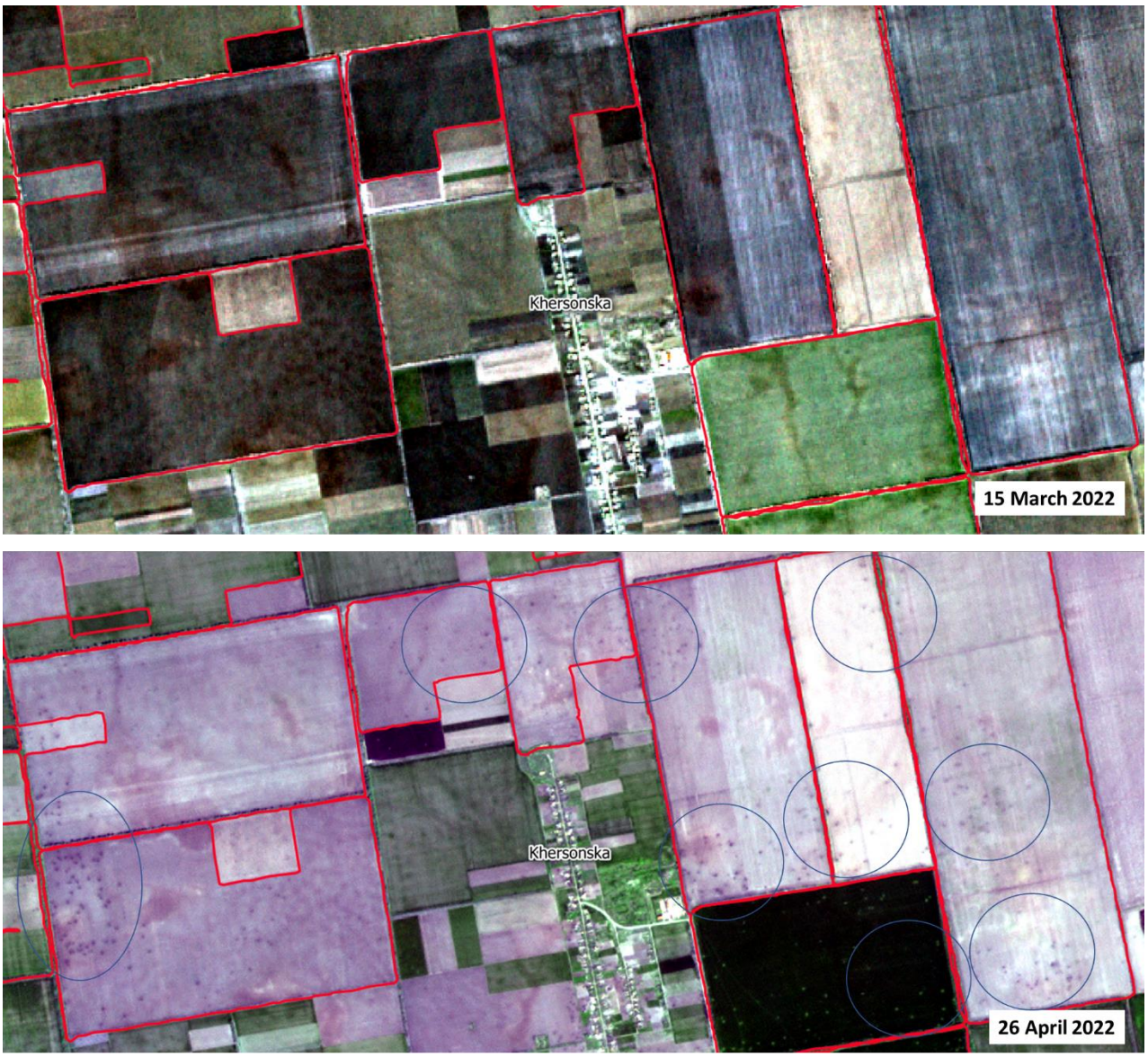


Damage of winter crops fields due to artillery fighting, Velykopysarivska OTG

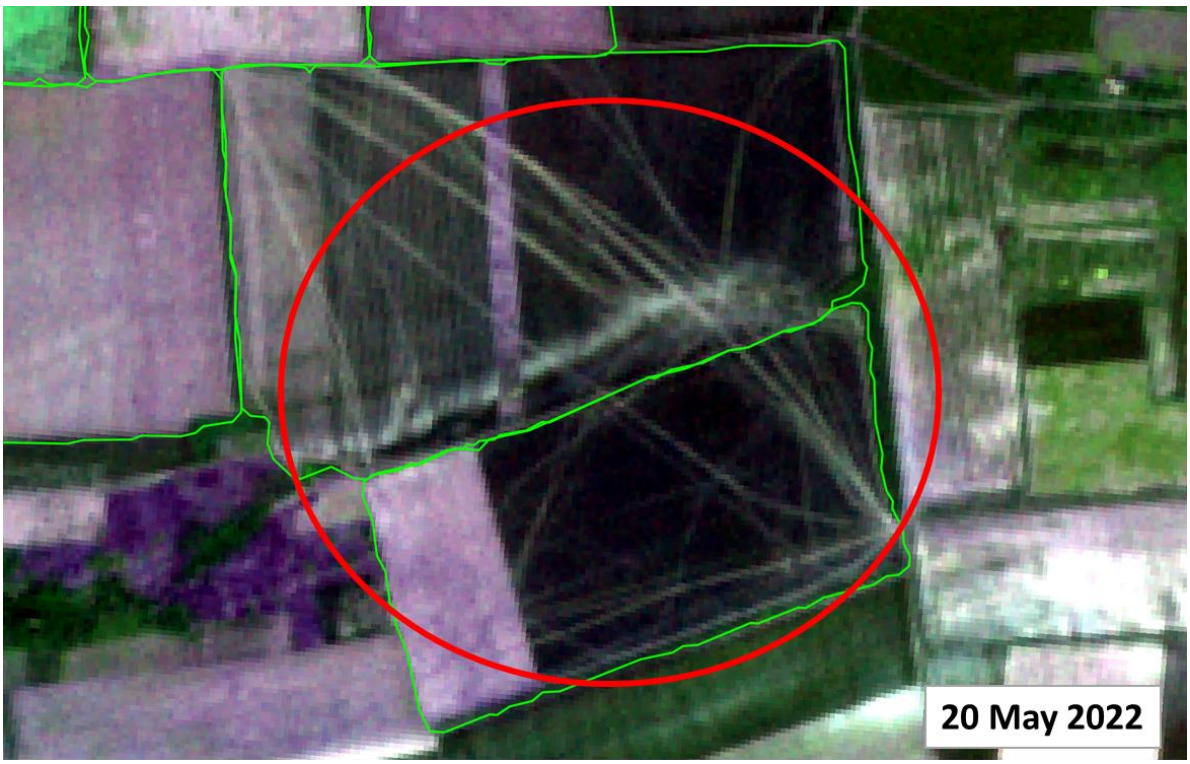
Damage of fields due to artillery fighting, Zaporizka oblast, Vasylivskii region, Stepnohirska OTG



Damage of fields due to artillery fighting, Mykolaivska oblast, Mykolaivskii region, Pervomayska OTG



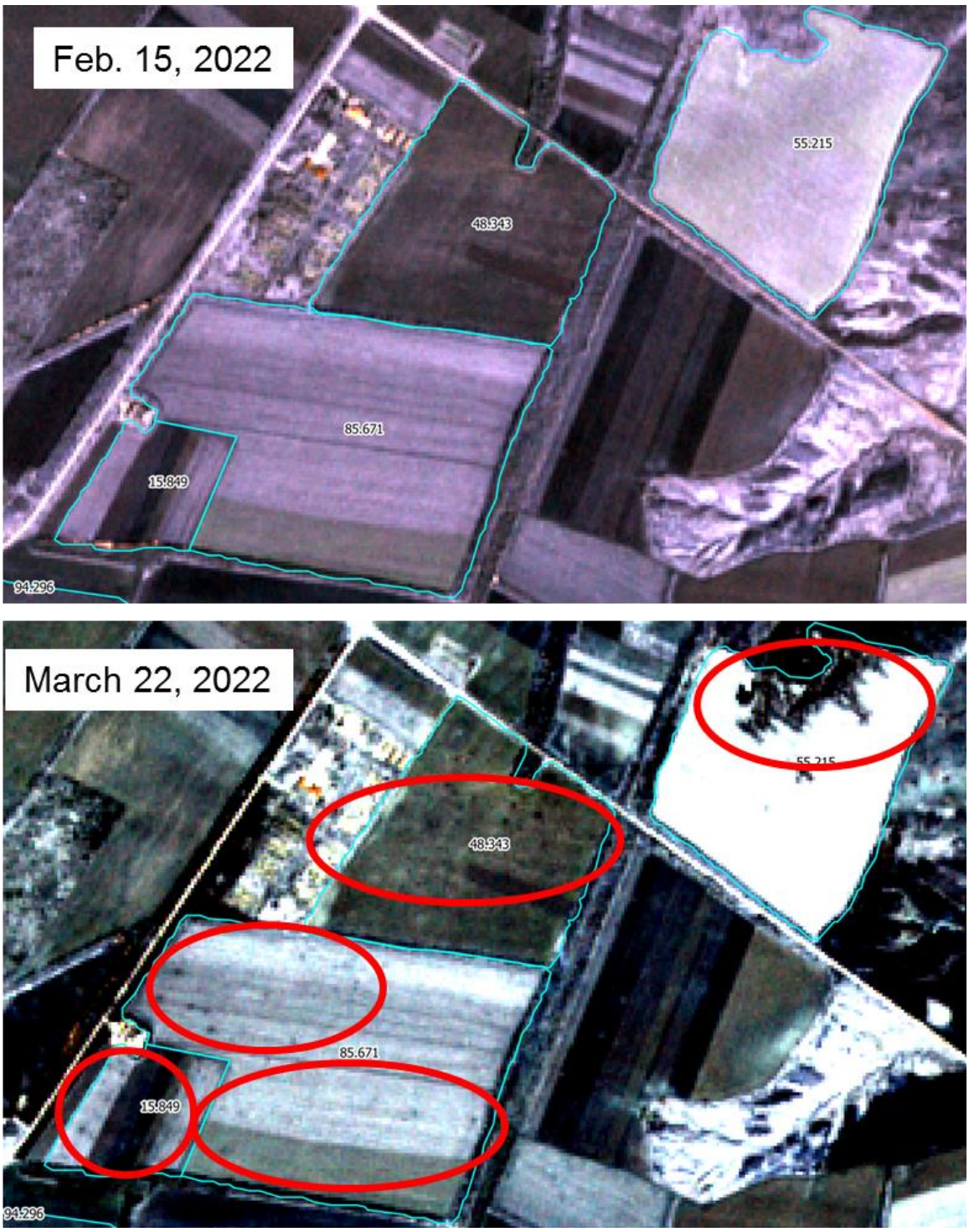
Damage of fields due to artillery fighting, Khersonska oblast, Beryslavskii region, Novovorontsovska OTG



Damage from military equipment, Zaporizka oblast, Vasylivskyi region, Vasylivska OTG

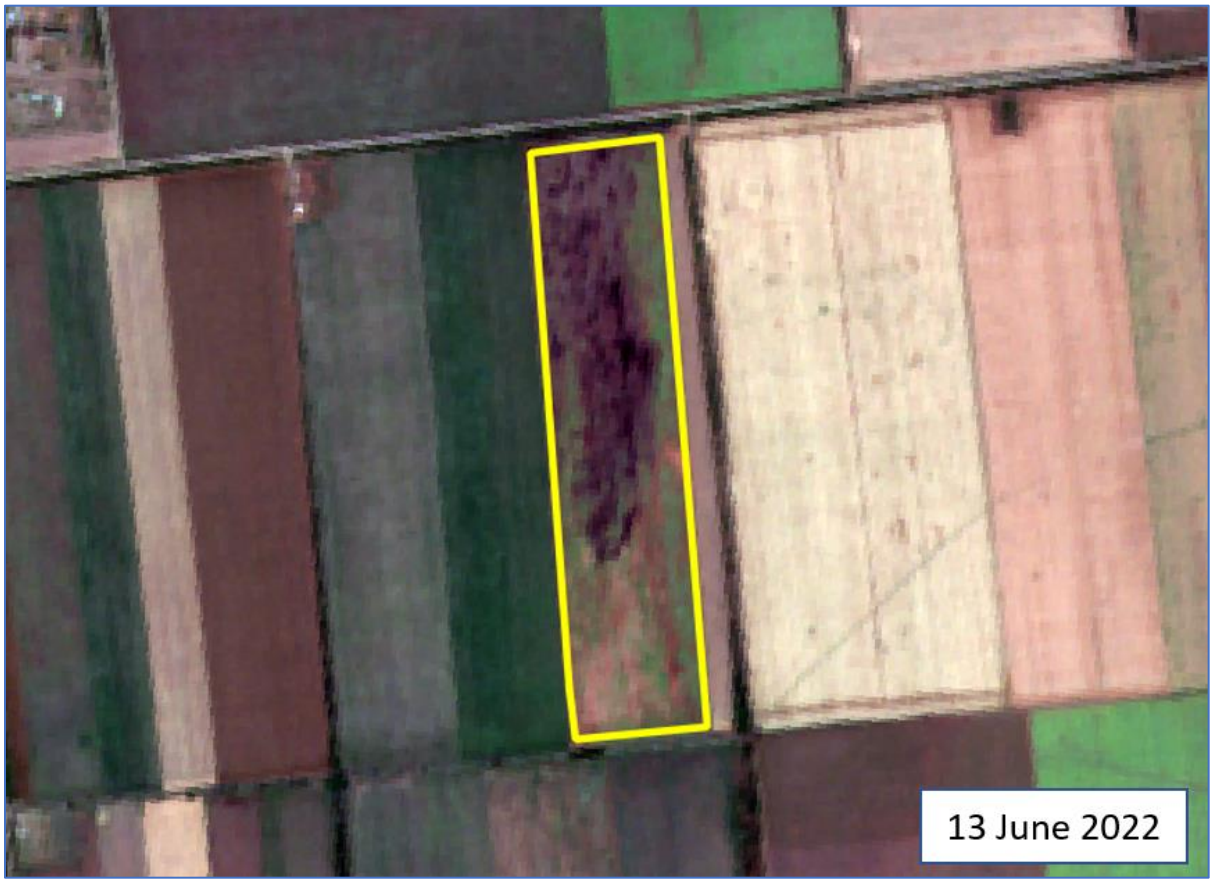
Damage of fields due to artillery fighting, Mykolaivska oblast, Bashtanskyi region, Shyrokivska OTG

Damage of fields due to artillery fighting, Vasylivska OTG

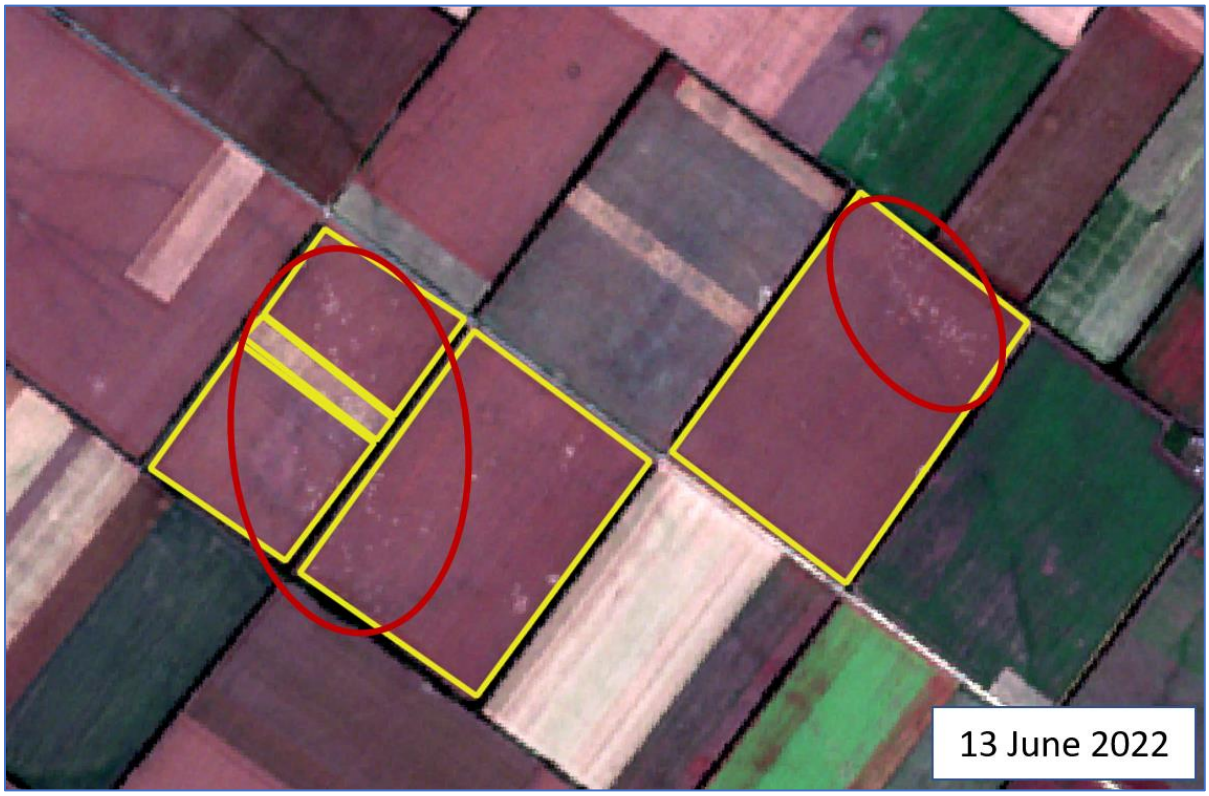


Damage of fields due to artillery fighting and to stubble burning (may be caused by an artillery shell, rockets or aircrafts wreckage, etc.), Orhivska OTG

Damage of fields due to artillery fighting, Mykolaiv oblast, Bashtansky region, Snigupivska OTG.



Burned crops, Kharkivska oblast, Izumivskiy region, Oskilska OTG.



Damage of fields due to artillery fighting, Mykolaiv oblast, Bashtansky region, Snigupivska OTG.

Damage to the surface of the field due to the movement of armored vehicles, Kherson oblast, Beryslav region, Kalinovskaya OTG.

Burned crops, Kherson oblast, Kherson region, district Belozepska OTG.

Extensive damage of fields due to artillery battles, movement of armored vehicles and fires, Kherson oblast, Kherson region, Stanislavskaya OTG.

Damage to the surface of the field due to the movement of armored vehicles, Zaporizhia oblast, Pologi region, Malynivska OTG.