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A semi-supervised multi-sensor remote sensing pipeline for mapping irrigation dynamics in ground-truth deficient conflict zones: a case study of the Kakhovka Dam failure

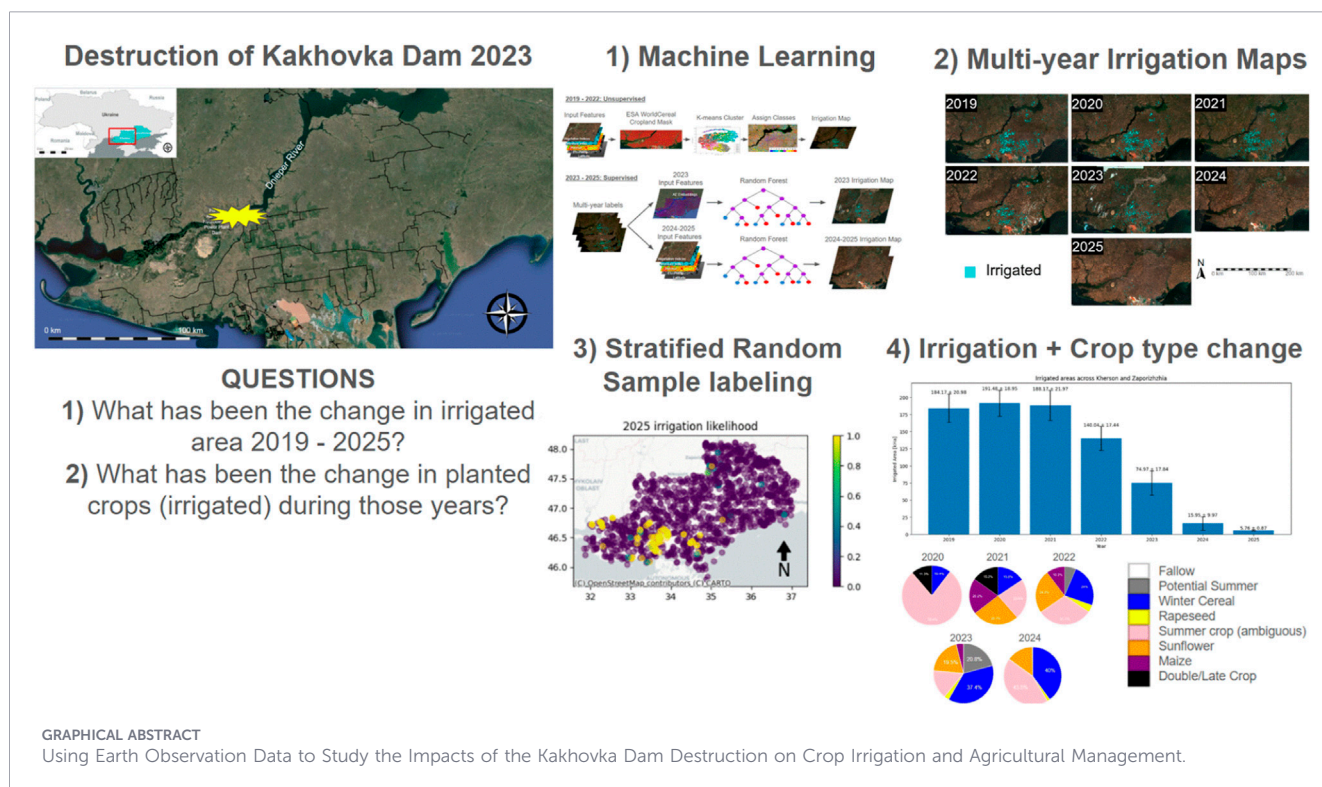
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The ongoing war in Ukraine has drawn international attention to the impact of conflict on global agricultural production and food security. On 6 June 2023, the Kakhovka Dam was destroyed. The loss of this critical agricultural and energy infrastructure has left most farmers on the East bank of the Dnipro River without irrigation in Kherson and Zaporizhzhia oblasts. This study develops a multi-sensor Earth Observation framework combining high resolution satellite imagery (Sentinel-2, Landsat) with meteorological data (CHIRPS) and water productivity data (FAO WaPOR), using a semi-supervised machine learning pipeline. Using a rigorous stratified random-sampling approach with photointerpretation, we found pre-war irrigated areas between 2019 to 2021 to be on average 187.94 ± 14.43 kHa, approximately 4% of pre-war baseline cropland and 8% of summer season cropland in Kherson and Zaporizhzhia oblasts. In 2022, these numbers contracted to 140.04 ± 17.44 kHa with the expanded occupation of these territories by Russia, seeing an additional decline in 2023 to 74.97 ± 17.84 kHa. Fields in 2023 also exhibited variability in irrigation, ranging from interrupted irrigation owing to the destruction of the Kakhovka reservoir, to those that were sufficiently irrigated with water remaining in the channels. Irrigated areas diminished further in 2024 to 15.95 ± 9.97 kHa, a ~91% decline from pre-war averages. Based on inspection, formerly irrigated fields before 2023 were either systematically abandoned or converted to winter cropland with lower input requirements by 2024—a pattern that continued into 2025 (total irrigated area 5.76 ± 0.87 kHa). This study demonstrates the power of advanced EO workflows to precisely quantify agricultural transformation and infrastructural failure in ground-truth deficient, high-risk environments.

KEYWORDS

agriculture, earth observation, evapotranspiration, irrigation, Ukraine



Highlights

- The Kakhovka reservoir, which supplied water to ~200 kHa of agricultural lands in Kherson and Zaporizhzhia, was destroyed on June 6, 2023
- We assess the agricultural impact of the Dam's destruction on the irrigation infrastructure in the region using Earth Observation
- Significant loss in irrigation between the pre-full-scale invasion years (2019–2021) and post full-scale invasion years, with a near total loss by 2025, are observed
- Fields that used to be irrigated for summer-crops are observed switching to winter crops that do not require as much irrigation

1 Introduction

The Russian invasion of Ukraine, which began in 2014 and expanded in 2022, has caused widespread destruction of agricultural lands in Ukraine (Wagner et al., 2026). Given the security situation of active warzones, satellite Earth Observation (EO) remains among the main methods to monitor the impact of war on agricultural production and food security (Baumann and Kuemmerle, 2016). Wagner et al. (2026) used Planet 3 m imagery to document the impact of the ongoing war on crop planted and harvested areas, especially devastated along the frontline. Preliminary results from NASA Harvest, NASA's Global Agriculture and Food Supply Consortium, estimated that 2.1–2.8 million hectares of agricultural land have ceased production from the war (Farming Amidst a War: Satellite Data Reveals Productive Yet Challenging

Season for Ukraine, 2026; Skakun et al., 2022) used VHR imagery and deep learning methods to identify over 1 million artillery and rocket craters across 21,500 square kilometers of agricultural land Donetsk, Luhansk, Kharkiv, Zaporizhzhia, and Kherson oblasts, which may contain unexploded ordnance that will pose as persistent hazards after the war. According to the Third World Bank Rapid Damage and Needs Assessment (RDNA3), agricultural damages and losses suffered by Ukraine up to December 2023 were estimated at US\$80.1 billion (World Bank, 2024a).

A major escalation of this assault on Ukrainian agriculture occurred on 6 June 2023, with the collapse of the Kakhovka Dam. A Soviet-era construction completed in 1956 (Hapich and Onoprienko, 2024), the Kakhovka Dam had supported the 2155 km² Kakhovka Reservoir, a source of water and power for 700,000 people and approximately 260 kHa of irrigation-enabled fields). The draining of the Kakhovka Reservoir flooded 73 kHa downstream (Rosa et al., 2024). The loss of this critical agricultural and energy infrastructure left farmers on the Eastern bank of the Dnieper River without irrigation in the historically arid Kherson and Zaporizhzhia oblasts (Vyshnevskiy et al., 2023). The World Bank RDNA 3 estimates the resulting damage to the agriculture and water sector to be US\$359.3 million, not accounting for the loss of irrigation in the 2023 and 2024 season (World Bank, 2024a).

Previous studies assessing the impact of Kakhovka have focused on the immediate aftermath of the dam collapse, such as the flooding extent, the environmental consequences (Naddaf, 2023) and rapid assessment of infrastructure damage (Matiash et al., 2023; Dari et al., 2024)) attempted to quantify the change in water consumption in the region using an inversion method with Sentinel-1 derived soil moisture. However, the 1 km spatial resolution of the resulting map

provides a coarse assessment of the impact and is not applicable for field-scale analysis of irrigation loss (Rosa et al., 2024). provided an analysis of irrigation extent across Ukraine for 2022, and policy guidance on post-invasion reconstruction for Ukraine to mitigate the water scarcity impacts of climate change. At the same time, the change in irrigation extent following the dam collapse, and its impact on the 2023 and 2024 seasons, were not within their scope. The more recent study by (Yailymov et al., 2025) reckons the irrigated area (both winter crops and summer crops) of Kherson in 2024 to be 38kHa—however, this number excludes Zaporizhzhia and does not have an uncertainty value arising from map biases.

Irrigation refers to the practice of artificially supplying water to agricultural land. A significant Earth system process, irrigation accounts for nearly 70% of human freshwater withdrawals (Campbell et al., 2017). Irrigation expands the areas that can be cultivated, mitigates the effects of droughts, and increases yield in regions limited by rainfall (McDermid et al., 2023). Irrigation statistics of area and intensity can inform policy decisions on water management, food production, and land use (McDermid et al., 2023)—motivating the use of EO to monitor the practice.

EO detection of irrigation is broadly focused on irrigation classification (irrigated vs. rainfed) and irrigation quantification (water consumption), which are expounded upon in the review by (Massari et al., 2021) spanning across sensor types, methods, and geographical settings. The most frequently used sensor types and their associated irrigation features are optical (with an emphasis on vegetation indices), microwave (with an emphasis on soil moisture) and thermal (with an emphasis on land surface temperature) (Massari et al., 2021). The latter, combined with land surface models, can lead to derived products such as evapotranspiration which provides insights on water consumption by irrigated croplands (Massari et al., 2021).

While not exhaustive, the following studies are notable in the optical and thermal features used. In a study of 34 years of irrigation in the High Plains of the United States using Landsat data (Deines et al., 2019), developed the Neighborhood Greenness Index (NGI), a ratio between pixel Green Chlorophyll Vegetation Index (GCVI) (Gitelson et al., 2003) and neighboring GCVI within a 50 km radius with a percentile threshold. The global irrigation detection efforts of European Space Agency (ESA) World Cereals Phase 1 incorporated vegetation index percentiles, the difference between air temperature and land surface temperature, and derived evapotranspiration and soil moisture into a CatBoost model (Van Tricht et al., 2023). In analyzing the 20-year irrigation dynamics in the Contiguous United States at 30 m resolution (Xie et al., 2021), incorporated 32 inputs of Landsat derived indices and their percentiles, meteorological variables, soil water content, and static environmental variables such as distance to major rivers and slope.

Evapotranspiration (ET) is another crucial variable for irrigation detection, as it is a measurable quantity of plant water consumption. The measurement of ET from space-based sensors often involves the use of land surface energy balance models, with temperature data as input (Allen et al., 2007). In the realm of irrigation detection, ET has typically been used in comparison to baseline water consumption, indicated by precipitation and ET of similar neighboring regions (Brombacher et al., 2022). The spatial comparison between irrigated

field ET and surrounding areas has also been used to quantify water consumption (e.g., (Bretreger et al., 2022; Brombacher et al., 2022; Kragh et al., 2023).

Still others have attempted to incorporate microwave-derived inputs such as soil moisture, with an emphasis on measuring irrigation timing and quantification based on changes in soil water content. Much of this work has been done in Europe, utilizing Sentinel-1 derived soil moisture (Le Page et al., 2023; Zappa et al., 2024) in an effort to capture finer spatial scale dynamics (Brocca et al., 2018; Dari et al., 2020; Lawston et al., 2017).

A significant barrier for irrigation detection using EO has been paucity of training and validation data. The Global Map of Irrigated Areas (GMIA), the first attempt to digitize “Areas Equipped for Irrigation” (AEI), used national statistics (Döll and Siebert, 2002). GMIA and its successors (Siebert et al., 2013) have been used as proxy ground truths for supervised methods, such as (Nagaraj et al., 2021). However, there can be significant differences between nationally reported AEI and active areas of irrigation, as pointed out by (Massari et al., 2021). Though AEI has been seen to decline in Ukraine in recent updates (Mehta et al., 2024), the spatial coarseness of nationally reported statistics reduces its applicability in high resolution irrigation mapping, especially in a rapidly evolving conflict setting. In Europe, the Joint Research Centre (JRC)’s multi-year (2006–2022) LUCAS dataset has compiled 20,995 points of irrigation across the continent (d’Andrimont et al., 2020). Though Ukraine is not covered in LUCAS, similar agrometeorological regions exist in Ukraine, lending itself to potential future transfer models.

In this study, we use Earth observation (EO) data to assess the change in irrigation coverage in the occupied regions resulting from the loss of the dam, accounting for the lagging impacts 1 year later.

Two key research questions drive this investigation:

1. What has been the impact of the Kakhovka Dam destruction in 2023 on the irrigation in the region?
2. How has the cropping pattern in Kherson and Zaporizhzhia changed after the collapse of the Kakhovka Dam?

2 Materials and methods

2.1 Study area

The study region encompasses Kherson and Zaporizhzhia oblasts of southern Ukraine, which have been partially occupied by Russia since 2022, as documented by United Nations General Assembly Resolution ES-11/4 (Territorial Integrity of Ukraine: Defending the Principles of the Charter of the United Nations: Resolution/, 2022). The Köppen-Geiger classification for this region is mainly cold semi-arid (BSk) (Beck et al., 2023), and the mean annual precipitation is ~400 mm/year, of which ~50 mm falls during June, and the growing season temperatures can reach a peak of ~30 °C by July (World Bank, 2024b).

As a historically semi-arid region, agriculture intensified in the area with the establishment of extensive irrigation networks in 1960s–1980s for state-run farms under the Soviet Union (shown in Figure 1), which at its peak boasted 2.2 million irrigated hectares

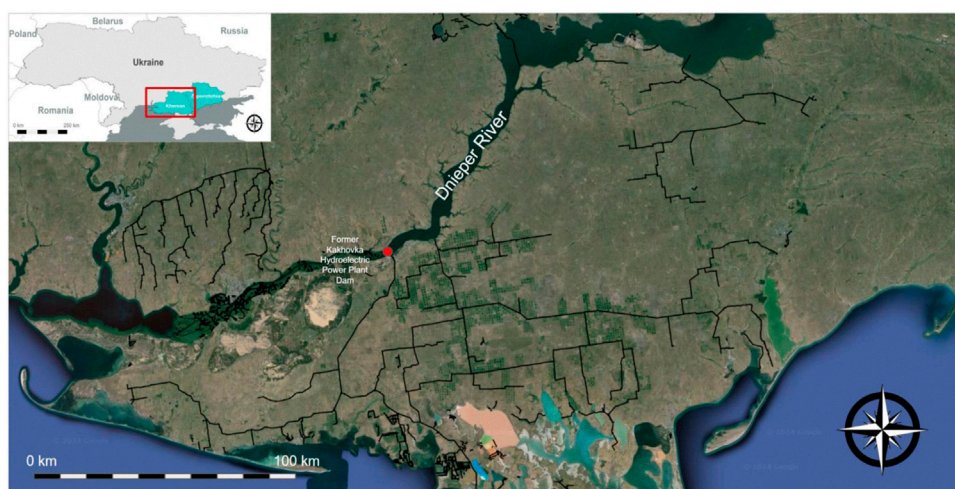


FIGURE 1
Canal networks and waterways in Southeastern Ukraine (Kherson, Zaporizhzhia) prior to the collapse of the Kakhovka dam (in red). Canal network courtesy of Open Street Map (Ukraine Waterways, 2026), baselayer from Google (Imagery Landsat / Copernicus) prior to dam collapse in 2023.



FIGURE 2
PlanetScope imagery of irrigation canal networks before and after the Kakhovka dam destruction on 6 June 2023, shows formerly dark, filled canals turn to dry canals in 2024 (46° 42' 42.41" N 33° 22' 20.85" E).

across Ukraine (World Bank Group, 2017). The collapse of the Soviet Union and lack of maintenance resulted in the decline to an irrigation capacity of 370 kHa by 2013, of which 261 kHa was actually irrigated (World Bank Group, 2017). Most of the water used for irrigation is derived from surface water, most notably the Kakhovka Reservoir, and is managed by the State Agency for Water Resources of Ukraine (SAWR) (World Bank Group, 2017).

The primary crops being irrigated are summer crops such as soy, maize, sunflower, and vegetables, typically cultivated from March to October (USDA Foreign Agricultural Service, 2026). We note that irrigation can take many forms and be applied at all spatial scales of fields—and for the purposes of this study constrain our scope of irrigation to large-sized fields detectable on the scale of Landsat pixels, 30 m resolution.

Additionally, given the focus to measure the impact of Kakhovka Dam collapse on irrigation capacity (as shown in Figure 2) and agricultural production in Southeastern Ukraine, we constrain our observation period to the later part of summer, after dam collapse, between July and September. This part of the growing season typically corresponds to the flowering stage of staple crops such as maize (USDA Foreign Agricultural Service, 2026) and oil crops such as sunflowers (Qadir et al., 2023).

2.2 Data

While ground truth is unavailable for the occupied territories, the NASA Harvest Ukrainian Partnership obtained multi-year (2021–2023) boundaries of irrigated fields from private partners in Ukraine, primarily in Poltava, Cherkasy, and Zhytomyr oblasts covering the years 2021–2023, away from the frontlines. Given the relatively small sample size ($n = 171$), and the different climate regimes from the study areas of Kherson and Zaporizhzhia oblasts, these data were reserved for feature selection development, and not used in the model training. The following input features in Table 1 were used for irrigation classification based on the physical characteristics of irrigated fields that differentiate them from rainfed fields. All input features were resampled to 30 m resolution for classification.

To isolate the effect of Kakhovka Dam collapse on irrigation extent, the growing season is bisected to the following time periods: a) *Pre-dam collapse* and the immediate aftermath including the month of June, b) *Post-dam collapse*, start of July to start of September. Consulting the USDA crop calendar for Ukraine, July aligns with the harvest period for winter crops and the vegetative and flowering period for main-season crops corresponding to the

TABLE 1 Input features for classification.

Data Source	Variable	Spatial Resolution [m]	Rationale
Landsat	Seasonal mean LST (normalized)	100 (resampled to 30 m)	Irrigated fields are more likely to be cooler than rainfed fields
Sentinel-2	Bands 2–8	10 (Bands 2-4, 8, resampled to 30 m) 20 (Bands 5-7, resampled to 30 m)	Sentinel-2 Top of the Atmosphere bands relevant to vegetation and land cover analysis
	NDVI max	10 resampled to 30 m	Irrigated fields are greener than rainfed fields
	NDMI max	10 resampled to 30 m	Irrigated fields are likely to be more moist than rainfed fields
	GCVI max	10 resampled to 30 m	Irrigated fields are greener than rainfed fields
WaPOR v3 AETI (FAO, 2024) CHIRPS (Funk et al., 2015)	Evapotranspiration-Precipitation Ratio (ET-ratio)	300 (resampled to 30 m) 5500 (Ratio between AETI and Precipitation resampled to 30 m)	Irrigated field ET is more likely to exceed rainfed water availability

crop types most likely to be affected by the loss of irrigation (USDA Foreign Agricultural Service, 2026). The input features mentioned in Table 1 are thus constrained to the post-dam collapse period of July to September.

Irrigated fields are more likely to exhibit colder Land Surface Temperatures (LST) than non-irrigated fields (Deines et al., 2019). The thermal aspect of irrigated fields were captured using Landsat-8 and Landsat-9 Thermal Infrared Sensor (TIRS) B10, accessed via the available Landsat 8/9 Tier 1 Collection on Google Earth Engine (Gorelick et al., 2017). Post cloud masking using the quality bands, the seasonal mean temperature derived temperature was min-max (25 °C, 55 °C) normalized prior to clustering according to a zonal histogram of the study area. Observational gaps from Landsat acquisition were filled using the zonal mean temperature for each image within the study area.

The greenness and moisture aspect of irrigated fields were used as input features for clustering using Sentinel-2 derived Normalized Difference Vegetation Index (NDVI), Normalized Difference Moisture Index (NDMI), and the Green Chlorophyll Vegetation Index (GCVI).

Following cloud masking using the Cloud Score + product on Google Earth Engine (Pasquarella et al., 2023), the seasonal max was taken for each of these indices.

Another key input sought to proxy Evapotranspiration, (ET). The ET of irrigated plants is less limited by precipitation than rainfed fields, which is approximated using the ET/Precipitation ratio, the ratio between actual evapotranspiration and precipitation amounts in a time period (McDonald, 1961). In this study we use the following formulation (Equation 1) for the ET/Precipitation ratio:

$$\frac{ET}{Precipitation} Ratio = \frac{\sum actual\ evapotranspiration}{\sum precipitation} \quad (1)$$

To account for soil moisture latency from prior rainfall, cumulative precipitation is measured from the month prior to the starting month of the evapotranspiration product. High ET/Precipitation ratio indicates that actual evapotranspiration exceeded that expected from precipitation observed. A low ET/Precipitation ratio means that ET was either low due to low vegetation, or that precipitation sufficiently met the vegetation water requirements.

In calculating the ET/Precipitation ratio, the FAO WaPOR v3 Actual Evapotranspiration and Interception (AETI) was used (FAO, 2020). WaPOR AETI (FAO, 2020) is a global product derived from the Penman-Monteith Equation incorporating Earth Observation measurements of solar radiation and temperature (Bastiaanssen et al., 2012). In this study, the AETI product is bilinearly resampled from the native 300 m resolution to 30 m to lessen the effects of abrupt pixel value change on the downstream irrigation maps. We acknowledge that bilinearly resampling 300 m FAO WaPOR v3 AETI and 5.5 km CHIRPS grids to a uniform 30 m resolution introduces spatial smoothing and sub-pixel generalization. However, this spatial mismatch is mitigated by the structural characteristics of local irrigation layout. Historically, the Kakhovka network supplies large-scale, uniform center-pivot field blocks stretching up to ~1 km in diameter. Because water application is uniform across these expansive parcels, the macro-hydrological signal remains cohesive. This framework effectively combines the high temporal frequency of coarse thermal-meteorological grids with the crisp geometric borders of optical satellite sensors to generate a 30 m resolution irrigation map.

Figure 3, which shows the seasonal cumulative AETI values for the study region, illustrates the higher AETI rates of fields connected to the Kakhovka irrigation system, the higher AETI rates of the abnormally high precipitation year of 2021, and the overgrown frontline in 2022 and 2023.

Cumulative precipitation is derived from the Climate Hazards Infrared Precipitation with Stations (CHIRPS) dataset (Funk et al., 2015). Combined with the WaPOR AETI dataset, the ET/Precipitation ratio can be calculated, shown in Figure 4.

2.3 Classification

The irrigation classification process was two-fold. Given the lack of ground truth presence in an active warzone, an unsupervised approach with K-Means clustering (Arthur and Vassilvitskii, 2007) was taken to identify potentially irrigated fields in the years 2019–2022, which were then used as labels to classify a multi-year random-forest model (Breiman, 2001) to be applied in 2023 and 2024 –the years where active irrigation was not guaranteed given the collapse

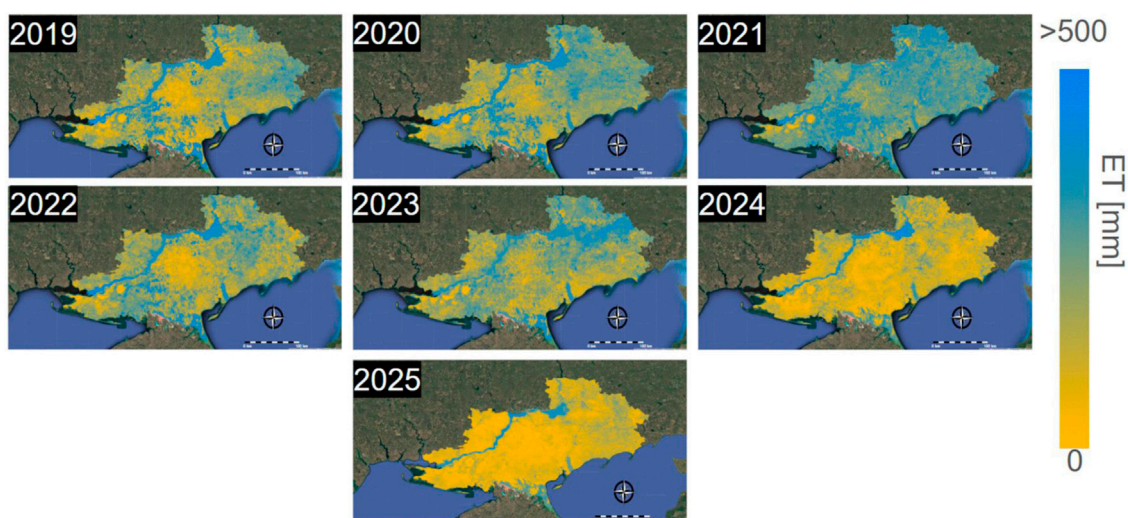


FIGURE 3
Seasonal (June - September) cumulative evapotranspiration over study duration in study region.

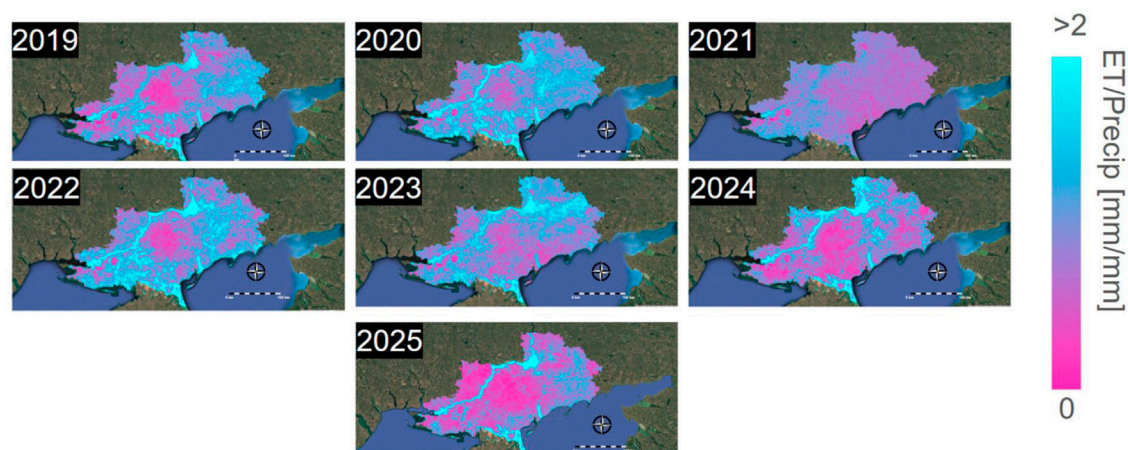


FIGURE 4
Seasonal (June - September) ET/Precipitation ratio over study duration in study region.

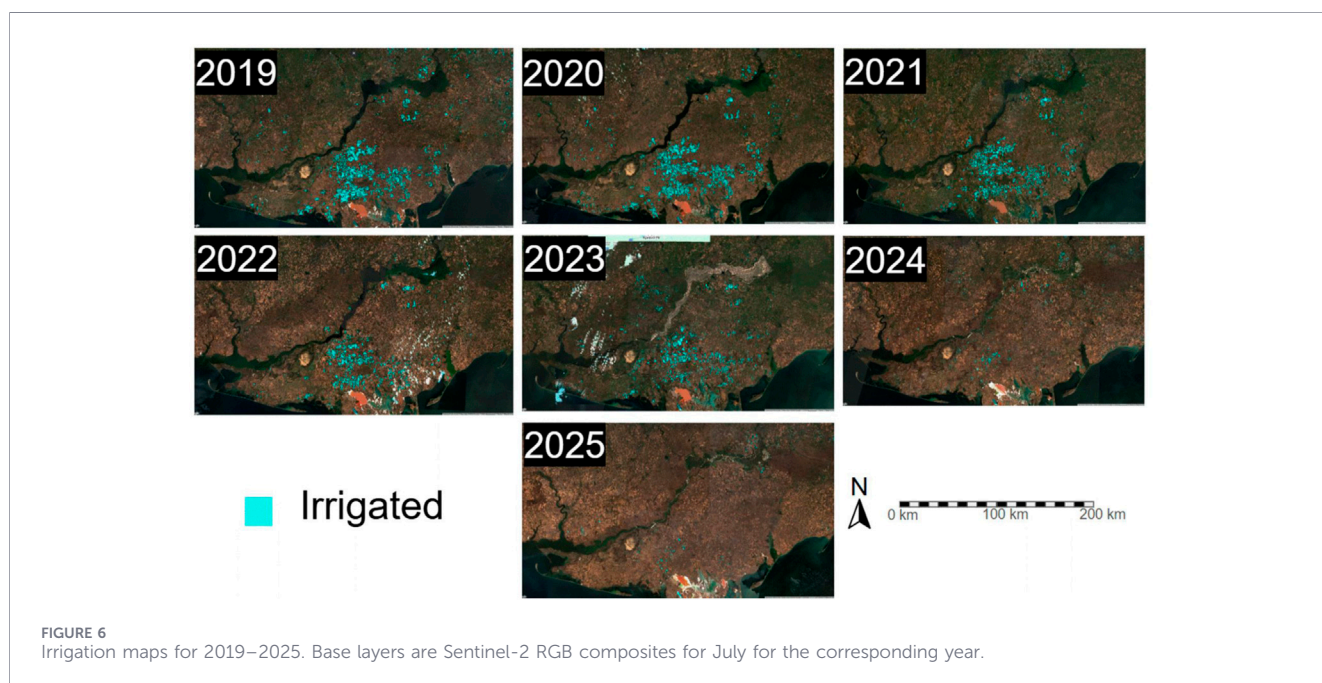
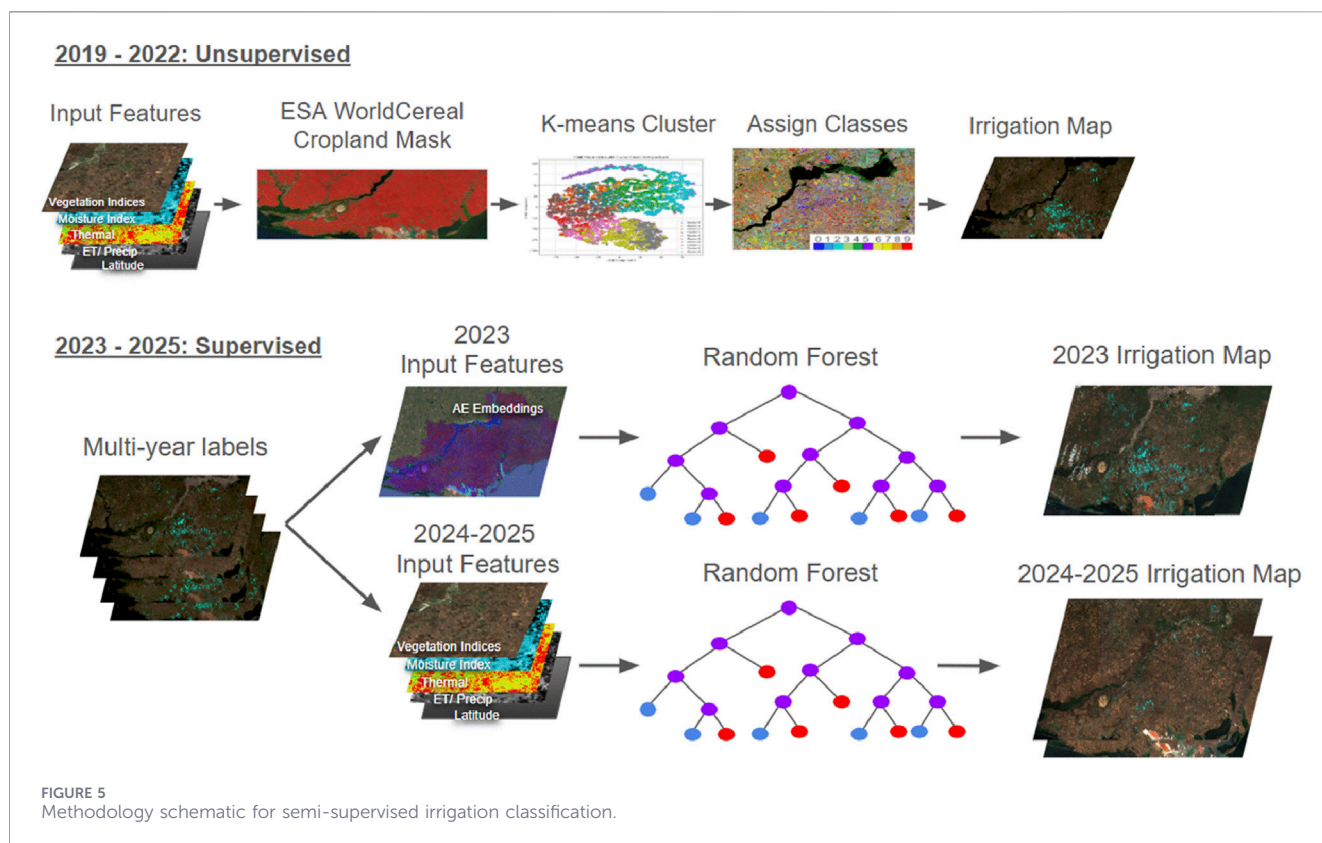
of the Kakhovka Dam. The method of combining labels derived from clustering, to be fed into a supervised approach, has been in part derived from the method used by (Wang et al., 2019).

The schematic for the classification process can be shown in Figure 5. The initial K value for clustering was chosen to be 9, to account for possible clustering by crop type (e.g. Maize, soybean, sunflower, winter crops, mixed vegetables, etc., as noted in (USDA Foreign Agricultural Service, 2026)) in addition to irrigation status. The clusters were then assigned irrigation status of 0 (non-irrigated) or 1 (irrigated) based on spatial overlap with known irrigated fields (such as those exhibiting pivots), proximity to canals, and inspecting the associated vegetation indices, evapotranspiration to precipitation ratio, and thermal time series.

When needed, the clustering process was iteratively performed to isolate irrigated fields from those that may have been mistakenly classified. Such was the case in 2021 (shown in Supplementary

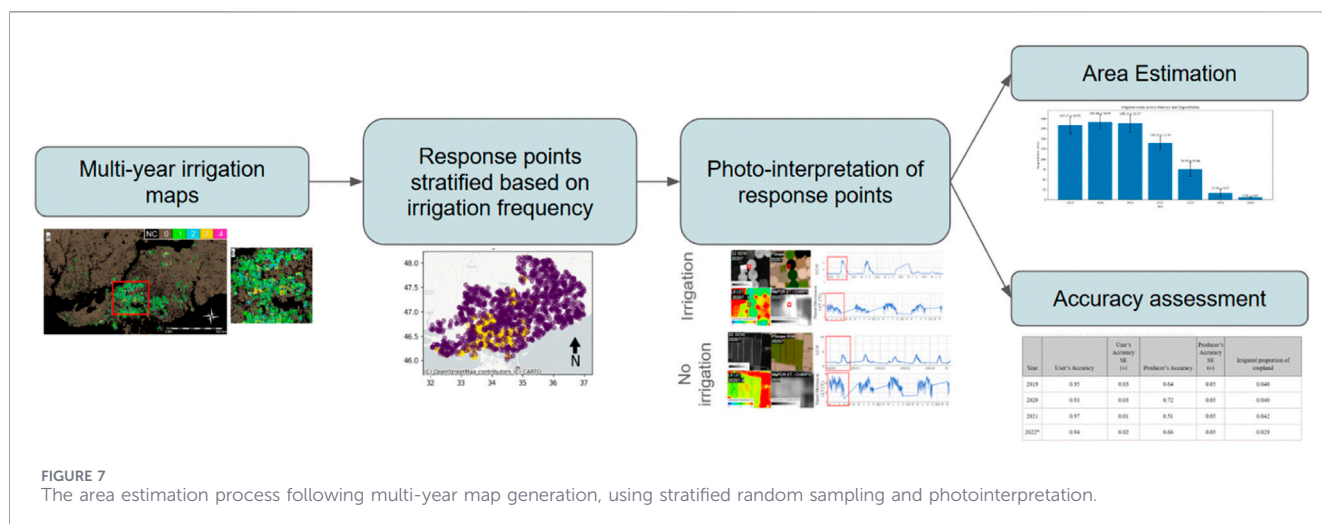
Figure S1), which experienced abnormally high precipitation events that could emulate irrigated conditions, and in 2022, which saw mass war-caused field abandonment and overgrown vegetation around the frontlines. Separating out rainfed crops from irrigated crops for 2021 entailed investigating the ET/Precipitation ratio, with higher ET/Precipitation ratios signaling higher likelihood of irrigation.

The clustering-based irrigation maps for 2019, 2020, 2021, and 2022 were then used as labels to train a random forest model (300 trees, 4 variables per split) to be applied to 2023, 2024, and 2025, using the same input features as during the unsupervised clustering step. A supervised approach was taken for these later years due to anticipated irrigation distribution shift and class imbalance. The annual irrigation maps are shown in Figure 6 and visualize the reduction in irrigated fields starting in 2022, leading to a near-complete loss in irrigation by 2024.



For 2023, which exhibited a transition period between full-season irrigation and interrupted irrigation from the loss of the Kakhovka Reservoir, additional training data was added to account for the overgrown abandoned fields in the frontline that would exhibit wetter features than rainfed fields, and the “interrupted” irrigation case (see: [Supplementary Figure S5](#)) which might not be

present in previous years. For the purpose of mapping and estimating the area of irrigation, these “interrupted” fields were classified as irrigation despite their intermediate characteristics between irrigation and rainfed fields, as categorizing a separate “interrupted” class would require quantifying irrigation volume which is outside the scope of this study. To assist with classifying



these intermediate irrigated fields, we also used AlphaEarth embeddings from (Brown et al., 2025) to use latent global features for classification. The irrigation maps for 2024 and 2025 used the same input features as 2019–2022, as detailed in Table 1, without the addition of AlphaEarth feature embeddings, based on the premise that fields equipped for irrigation would be able to satisfy their irrigation requirements without interruption. Given the dryer conditions of 2024 and 2025, it was anticipated that a model trained during prior years would result in an under-classification of irrigation for 2024 and 2025. To mitigate these effects, we supplemented the automatically sampled training data with a small corpus (<500) of hand-labeled data (such as of frontline abandoned fields) for the supervised classification of 2023–2025 maps.

2.4 Area estimation

For area estimation, we followed the stratified random sample approach (Olofsson et al., 2014; Skakun, 2025; Stehman, 2014), visualized in Figure 7. This is a multi-step process using the generated multi-year irrigation maps as strata for randomly sampled points, also known as “response points.” Each of the response points were then labeled as “irrigated” or “not irrigated” via photointerpretation using relevant Earth Observation and meteorological features, across the duration of the study period (2019–2025). The results of the labeling process were then used to generate irrigation area estimation and accuracy assessments for the generated irrigation maps.

2.4.1 Stratification scheme for response points

To estimate areas of irrigated land, we used a sample-based stratified random sampling approach (Olofsson et al. (2014), Stehman and Foody (2019)). Irrigation frequency was chosen as to be the basis of stratification to reduce the total number of separate points to label across years, and to track potential drivers of change in irrigation by longitudinally looking at the same points. Irrigation frequency in the region is visualized in Figure 8. Optimizing the sample proportions for the standard error of the target area based on (Stehman and Wagner, 2024), a total of 1577 points were sampled, as shown in Table 2, with

additional points added for post-Kakhovka dam loss years (2023–2025) as needed to capture the minority irrigation class.

2.4.2 Photointerpretation of response points for validation

As there is no field-level ground truth available from the occupied territories, validation is based on Earth Observation photointerpreted reference samples. The irrigation status of each response point was derived from similar assumptions for classification input features, with the incorporation of additional datasets from Planet with higher temporal and spatial resolution (Dijkstra et al., 2023).

For 2023, when the Kakhovka dam collapsed in the middle of the season, some fields exhibited an early-season irrigated characteristic (colder temperature, higher vegetation indices) and transitioned to non-irrigated characteristics with warmer temperatures and lower vegetation indices (sometimes abandonment). These fields, which were at times classified as irrigated and at times classified as non-irrigated by the classifier, were identified as “partial irrigation” within the broader category of “irrigation.”

The thermal, optical, hydrological, and miscellaneous characteristics used to identify irrigated and non-irrigated points in the validation process are described in Supplementary Section S3: Photointerpretation characteristics used for validation.

2.5 Validation results

The above irrigation criteria was applied to each of the response points, with each point labeled according to irrigation likelihood, a semi-qualitative metric between 0 and 1 where 1 is most likely irrigated. Figure 9 shows the distribution of stratified random samples with initially assigned irrigation likelihood. Points with labels between 0 and 1 were further examined and reassigned to the binary classes of irrigated or non-irrigated.

2.6 Area estimation

Post-validation, bias-adjusted area estimates are calculated following (Olofsson et al., 2014) and (Stehman and Foody, 2019).

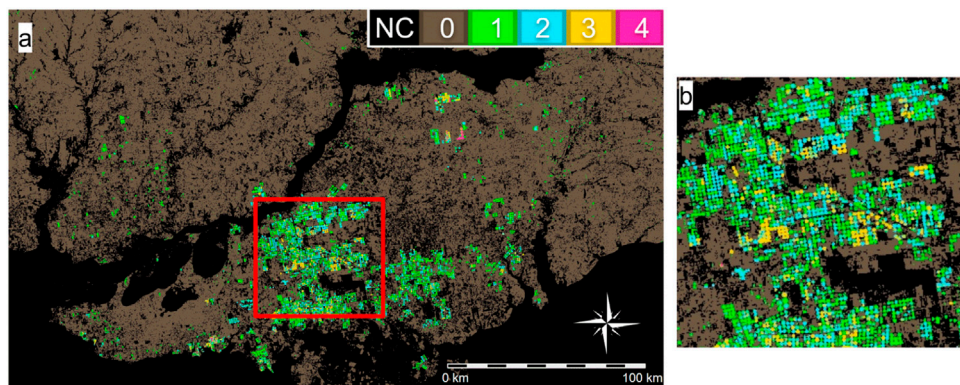


FIGURE 8
(a) Irrigation Frequency (2020–2023) strata for sampling, derived from classification results. NC = Not Cropland. (b) Zoomed in section of the red outlined region in subfigure a.

TABLE 2 Response points characteristics from stratified sampling according to irrigation frequency between 2020 and 2023.

Strata (h)	Area [kHa]	Stratum Weight	Pixel counts (K)	N sample (k)
–999	1838427.434	34.3%	20,412,531	107
0	3282703.922	61.3%	36480705	1046
1	141.19	2.64%	1,568,828	171
2	69.36	1.30%	770,666	135
3	23.06	0.43%	256,254	185
4	1.41	0.03%	15,686	36

As the stratification followed irrigation frequency, rather than the binary irrigation vs. non-irrigation classes on the annual maps, we took a post-stratification approach (Stehman, 2014) to estimating irrigation area for each year (Equations 2–5). We start by defining W_h , the weight (proportion of total map pixel count) for stratum h , calculated from the ratio between N_h (the total number of pixels in stratum h), and N (the total number of pixels):

$$W_h = \frac{N_h}{N} \quad (2)$$

Taking n_h to represent the number of samples in stratum h as opposed to out of the total population of pixels in the stratum (N_h), we further stratify the sample according to the target class for area estimation, c , such that:

$$n_h = \sum_{c=1}^k n_{h,c} \quad (3)$$

where K is the total number of classes and $n_{h,c}$ is the number of samples in stratum h and map class c . The area proportions of the class of interest, $\hat{p}_c$, is then calculated as:

$$\hat{p}_c = \sum_{h=1}^H W_h \frac{n_{h,c}}{n_h} \quad (4)$$

The corresponding variance for the area proportion of the target class is calculated as:

$$Var(\hat{p}_c) = \sum_{h=1}^H W_h^2 \frac{\left(\frac{n_{h,c}}{n_h}\right) \left(1 - \frac{n_{h,c}}{n_h}\right)}{n_h - 1} \quad (5)$$

With the resulting standard error being the square root of the variance.

2.7 Accuracy assessment

The accuracy assessment of the irrigated areas followed Stehman (2014), targeting the User's Accuracy (UA), and Producer's Accuracy (PA) with the use of indicator functions (Equations 6–12).

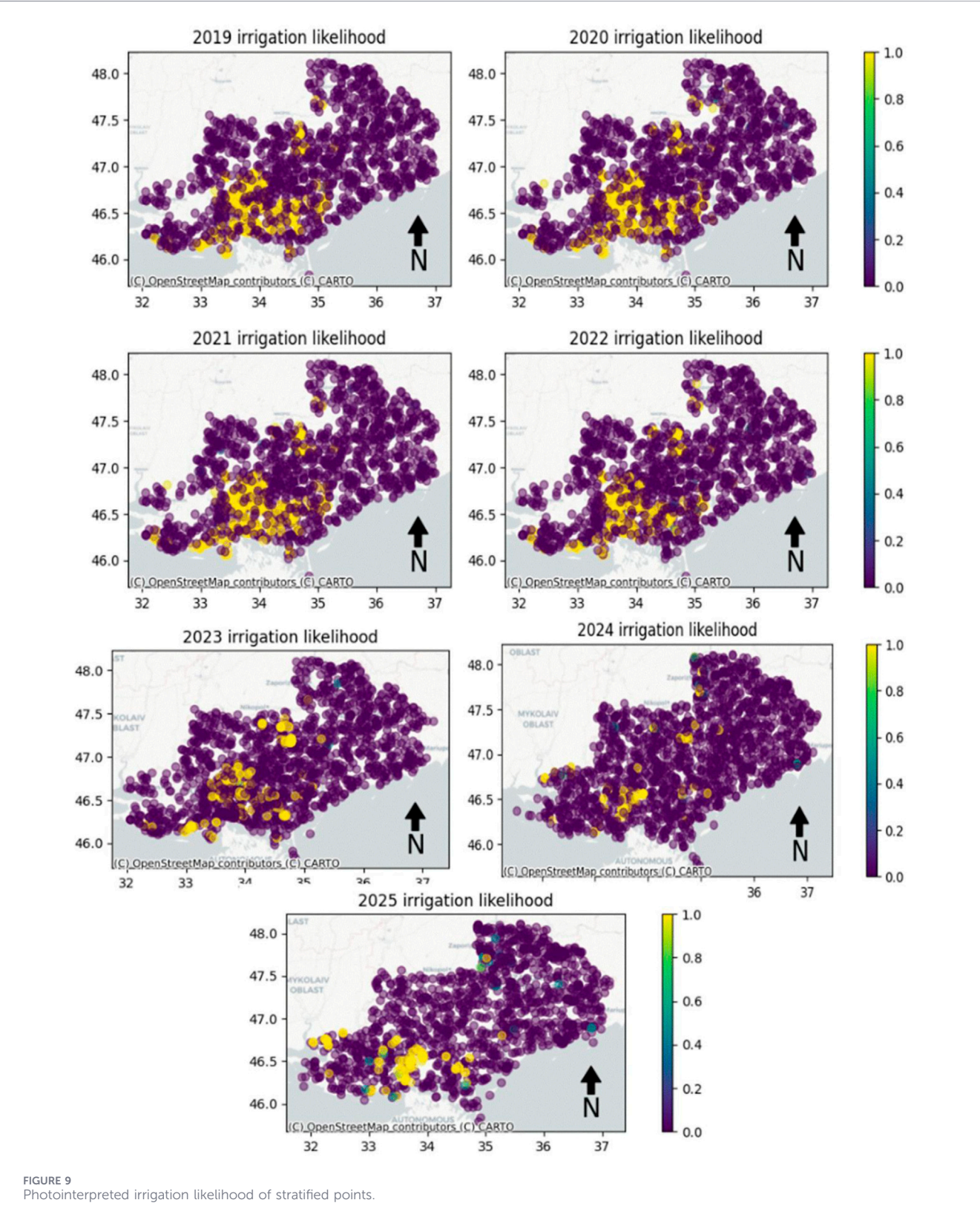
In the case of OA, the indicator function is:

$$y_u = 1 \text{ if pixel } u \text{ is reference class } k, 0 \text{ if pixel } u \text{ is not reference class } k \quad (6)$$

Which is then inserted into the area-based proportion with respect to the population of N pixels:

$$P_k^A \sum_{u=1}^N \frac{y_u}{N} = \bar{Y} \quad (7)$$

For UA, the indicator function is based on the map class and has an additional component, x_u :



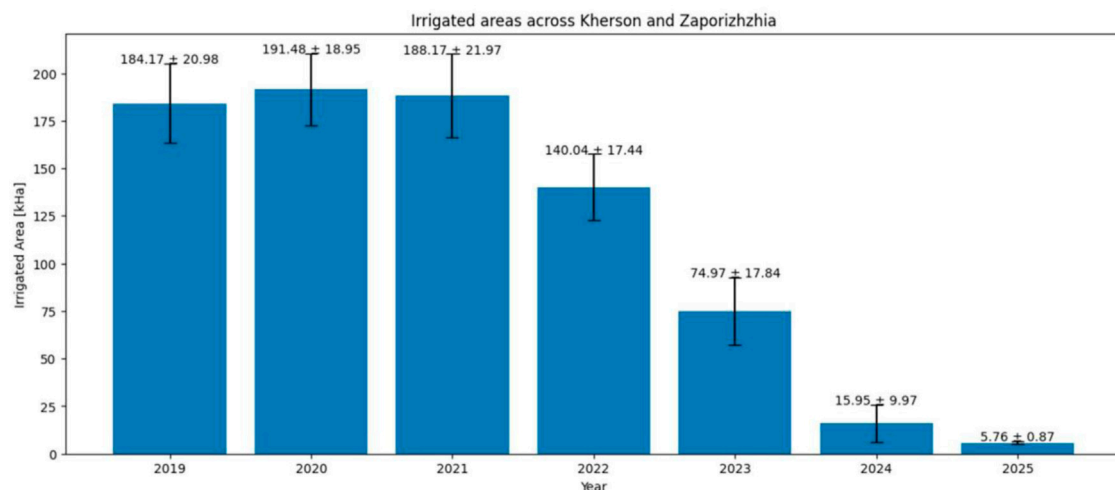


FIGURE 10
Area estimates of irrigated fields across Kherson and Zaporizhzhia. Error bars are 95% confidence intervals.

$y_u = 1$ if pixel u is classified correctly and has map class k , 0 otherwise,
(8)

$x_u = 1$ if pixel u is map class k , 0 otherwise.
(9)

Both y_u and x_u are inserted into a ratio:

$$R = \frac{\sum_{u=1}^N y_u}{\sum_{u=1}^N x_u}. \quad (10)$$

For PA, the indicator functions are based on the reference class and inserted to the same ratio as above.

$y_u = 1$ if pixel u is classified correctly and has reference class k ,
0 otherwise,
(11)

$x_u = 1$ if pixel u has reference class k , 0 otherwise.
(12)

The derivations of standard errors of the accuracies can be found in Stehman (2014), Equations 25–29.

3 Results

3.1 Irrigated area

We found a significant change in irrigated areas in the 6 years from 2019 to 2025 (Figure 10). Pre-war, irrigated areas between 2019 to 2021 were on average 187.94 ± 14.43 kHa, approximately 4% of pre-war 2021 baseline croplands (~5357 kHa) in Kherson and Zaporizhzhia oblasts (please refer to Supplementary Section 6 on the calculation for the multi-year average and uncertainty values). We note that the total cropland area in Kherson and Zaporizhzhia has likely also declined during the war, as evidenced by crop abandonment (Nair et al., 2026). These numbers decreased in 2022 to 140.04 ± 17.44 kHa with the expanded occupation of these territories by Russia, seeing an additional decline in 2023 to 74.97 ± 17.84 kHa. Irrigated areas decreased further in 2024 to

15.95 ± 9.97 kHa, a 91% decline from pre-war averages, and to 5.76 ± 0.87 kHa in 2025.

3.2 Irrigation map accuracy assessment

The results for the accuracy assessment using stratified random samples are shown in Table 3. It can be noted that the User's Accuracies (UA)s and Producer's Accuracies (PA) for 2023 (the transitional year marking the destruction of the Kakhovka Dam) and beyond are much lower than in previous years. For 2023, the presence of intermediate fields with interrupted irrigation led to model confusion. For 2024, where irrigation was a much rarer class than other years, there was confusion with colder, wetter fields in the northern part of Zaporizhzhia oblast—while at the same time, irrigation became a minority class of 0.3% (compared to 4% in pre-war years) of total cropland area. This was exacerbated in 2025, which experienced lower rainfall than previous years that led to further abandonment of typically rainfed summer fields. As such, the observed drops in UA and PA during these post-Kakhovka dam loss years reflect the severe class imbalance of irrigation compared to non-irrigation.

Critically, as demonstrated by Olofsson et al. (2014), our application of a post-stratified, sample-based area estimation framework mathematically corrects for these localized map classification biases. The resulting area statistics (e.g., 15.95 ± 9.97 kHa in 2024) remain statistically sound and unbiased, as the error margins account directly for the weights of each strata.

3.3 Crop type

Irrigation in Kherson and Zaporizhzhia is most frequently applied to soy, maize and sunflower (Rosa et al., 2024). While soy is listed as the top irrigated crop, the lack of a soy map in Ukraine requires us to use the summer crop mask to subsume soy statistics. It has also been pointed out by (Kussul et al., 2017) that soy is commonly confused with maize in Ukraine. For the years where maize and sunflower masks are available, they are separated from the

TABLE 3 User's, Producer' accuracies and their associated standard errors.

Year	User's Accuracy	User's Accuracy SE ($\pm$)	Producer's Accuracy	Producer's Accuracy SE ($\pm$)	Irrigated proportion of cropland
2019	0.95	0.03	0.64	0.05	0.040
2020	0.93	0.03	0.72	0.05	0.040
2021	0.97	0.01	0.51	0.05	0.042
2022*	0.94	0.02	0.66	0.05	0.029
2023*	0.56	0.07	0.69	0.06	0.014
2024*	0.21	0.13	0.58	0.29	0.00298
2025*	0.36	0.03	1	0	0.00155

*Years following the Russian full-scale invasion.

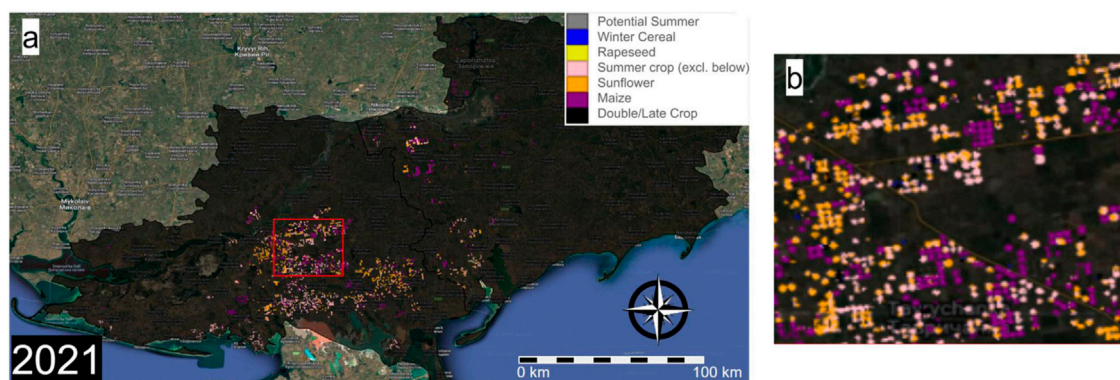


FIGURE 11 (a) Sunflower, maize, and other crop types are the vast majority of irrigated crops in Kherson and Zaporizhzhia oblasts (in black). Crop type map from NASA Harvest and ESA WorldCereal. (b) Zoomed-in section of the outlined box in subfigure a.

broader summer crop class (Qadir et al., 2023; Van Tricht et al., 2023; Wagner et al., 2026). A visualization of the irrigated crop types in 2022 is shown in Figure 11, while the irrigated crop type proportions for each year is shown in Figure 12. Tracking the fields that were irrigated at least once between 2020 and 2024 in Figure 13, it can be seen that there is a trend towards winter crops (such as wheat, barley, rapeseed) after the start of the war, with 2024 seeing more than 50% of the irrigated extent being cultivated with winter crops—an indication of a shift in crop type planting in response to loss of irrigation.

4 Discussion

Earth Observation, multi-stage classification, and robust photointerpretation for bias-adjusted area estimation were employed to map the locations of irrigated fields in Kherson and Zaporizhzhia across 7 years, from 2019–2025. The EO-based statistics show stable pre-war irrigated areas in Kherson and Zaporizhzhia, which declined after the Russian full-scale invasion in 2022. The loss of Kakhovka Dam and Reservoir led to an interruption of irrigation in 2023, followed by a nearly total loss of irrigated fields by 2024 and 2025. This is supported

by visibly dry irrigation canals in the region (Figure 2). In the 2024 season, it has been observed that fields once irrigated have been switched over to winter crops (such as wheat, barley, rapeseed), which do not require as much irrigation—an indication of farmers adapting to the loss of irrigation capacity. For 2025, there was a further reduction in irrigated area.

In comparing our results with those of previous studies (Rosa et al., 2024; Yailymov et al., 2025), we find our results to be lower, as shown in Figure 14. Compared to Rosa et al. (2024) who predict a combined irrigated area of 362 kHa for 2019, we report 184 ± 20.98 kHa, which is ~50%. Compared to the Yailymov et al. (2025) values of 351 kHa for Kherson alone, our combined Zaporizhzhia and Kherson values are 52%.

Both Yailymov et al. (2025) and Rosa et al. (2024) performed pixel-counting without a design-based area estimation, which leads us to assume that the biases of their models are unaccounted for in their area estimation. While our map accuracies were lower than those of Yailymov et al. (2025), we stand by the integrity of our area estimates based on our stratified random sampling approach and clear description of the validation process, described in Supplementary Section 3.

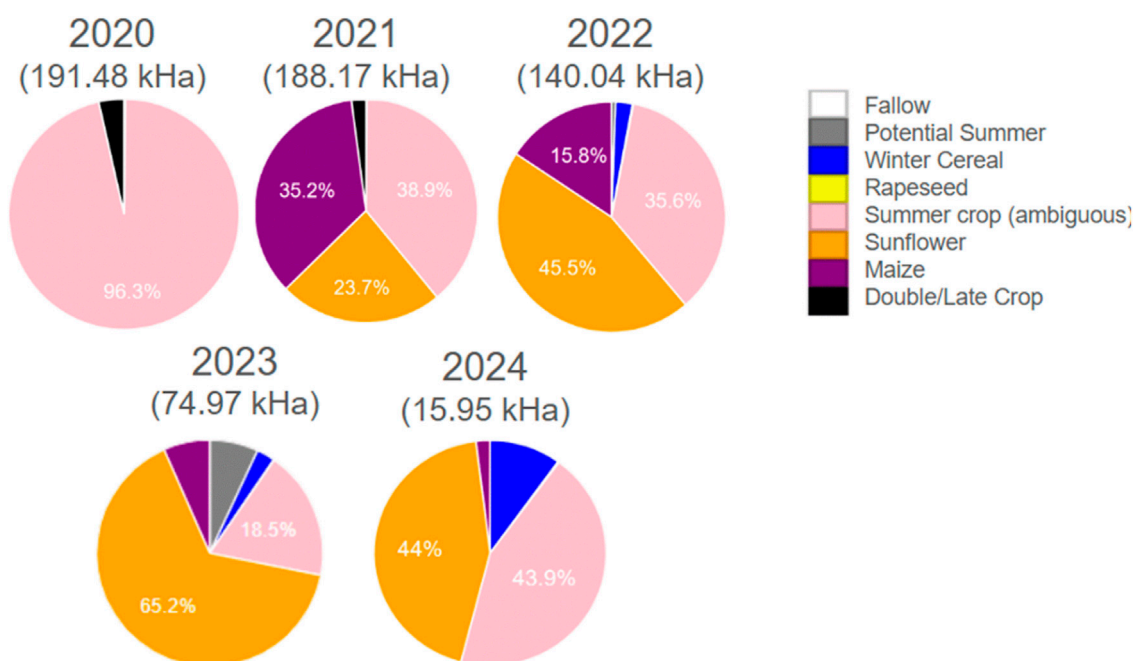


FIGURE 12
Irrigated crop type proportions for years with available crop type maps. For 2023, including partially irrigated regions.

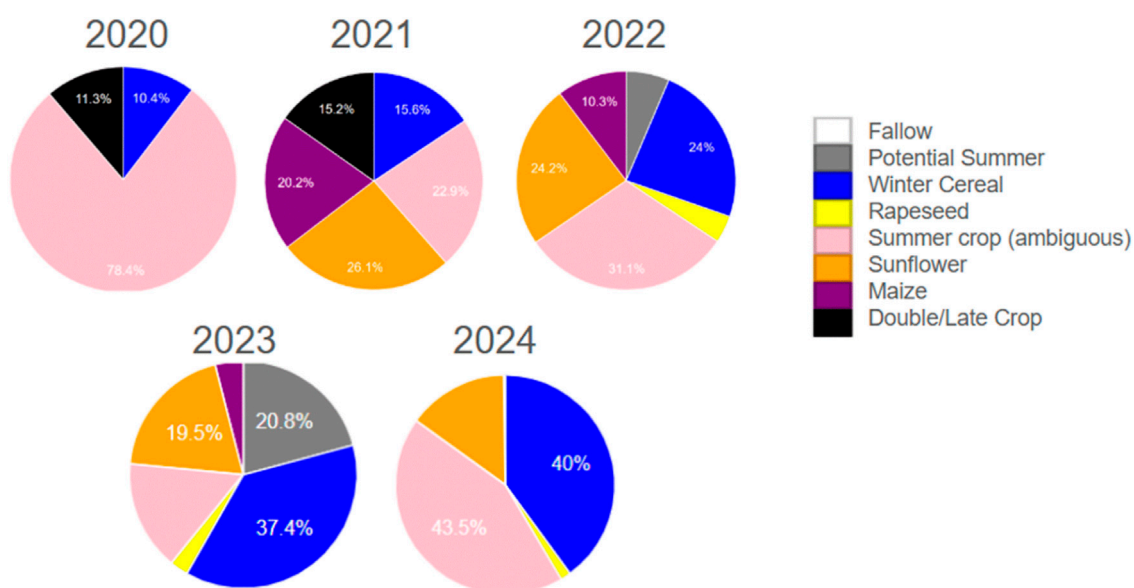
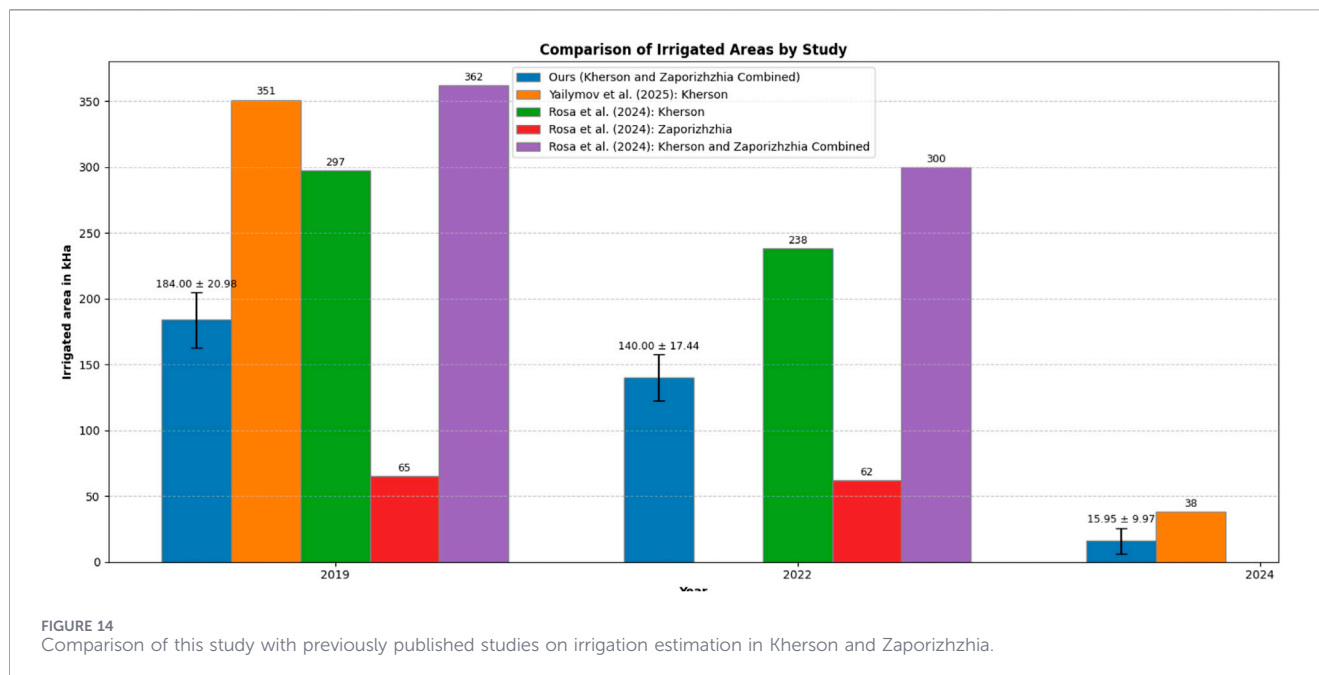


FIGURE 13
Annual crop types of irrigation-equipped fields that had been irrigated at least once between 2020–2024.

The World Bank RDNA3 estimates the recovery of the Kakhovka dam and pumping stations is estimated to cost ~ US\$1.5 billion (World Bank, 2024a). Such repairs, however, cannot be done in the ongoing conflict. This study, and the studies that may follow on irrigation damage caused by Kakhovka Dam collapse, could contribute to postwar discussions of reparations and reconstruction.

Regardless of the outcome of the war, Ukraine's agricultural infrastructure will need to be bolstered against the impact of climate change. The Coupled Model Intercomparison Project (CMIP) projections show a hotter and drier southern Ukraine with the greatest changes in Kherson, Zaporizhzhia, and Crimea oblasts (Eyring et al., 2016). In the near-term future of 2040–2059, the growing season (based on the interval between 6 consecutive



days above 5 °C) in these oblasts will be lengthened by 1 month compared to the historical baseline, and with a precipitation decline of ~ -26 mm (World Bank, 2024a). Rosa et al. (2024) anticipates that green water scarcity (GWS) necessitating irrigation will expand across much of southeastern Ukraine including most of Odessa and Mykolaiv oblasts in the 1.5 °C increase scenario. As part of their recommendations for reconstruction, Rosa et al. (2024) suggests decentralizing irrigation infrastructure across areas of need, as opposed to centralized systems like the former Kakhovka Irrigation network. Agnostic to the specific form that updated irrigation systems may take, monitoring capacity will be crucial to the maintenance of irrigation systems in Ukraine.

Several limitations need to be considered in this work. With the current conflict conditions near the front lines and the study region, we were unable to obtain ground truth of irrigated vs. non-irrigated fields in the occupied territories. The available ground truth provided by commercial partners situated in free-Ukraine provided insights for classification feature selection, however, they are located in a different agro-climatic zone from the study region of interest in Kherson and Zaporizhzhia oblasts. At the same time, it is also worth noting that irrigated fields exhibit similar characteristics to rainfed fields in colder climates, making the direct transfer of the classifier to cooler climate zones unadvisable. While Kherson and Zaporizhzhia cover limited latitude range, an irrigation classification model trained in this region may over-classify irrigation in northern latitudes. Models specific to different climate regimes or incorporating location information (such as in Deines et al., 2019), using latitude as a feature) will likely perform better than models attempting to generalize across large geographic and climatic regions. Another critical caveat accompanying this limitation is map accuracy (as can be observed by the low PAs and UAs in Table 3). As an extreme minority class (~4% total cropland area during pre-war years, down to less than 0.5% in

2024 onwards), the irrigation class is heavily penalized by omission and commission errors. As such, we advise potential users of the irrigation map to inspect local accuracy of the irrigation map before attempting to enforce field-level decision support or policy enforcement.

Additionally, while the study attempts to isolate the impact of the destruction of Kakhovka Dam by temporally constraining irrigation classification in July - September, the phenology of crops and the irrigation amount is dependent on finer meteorological conditions. For example, 2021 experienced much greater precipitation than in other years, and as such, farmers would have relied less on irrigation than in other years. However, the increased evapotranspiration and decreased temperature of 2021 could make differentiating irrigated fields from non-irrigated fields become more difficult in this situation. The study does not attempt to quantify the irrigation amount applied.

An area for improvement with respect to the input data for model classification is the spatial resolution of the evapotranspiration (300 m) and precipitation datasets (~5.5 km), which would make the irrigation detection pipeline more applicable to smaller fields than the large-scale pivot irrigation observed in Kherson and Zaporizhzhia. Finally, the use of stratification according to irrigation change class may be affected by errors in co-registration of Sentinel-2 can affect the irrigation status of a pixel from year to year.

Future work could incorporate high cadence EO-derived thermal, evapotranspiration, and soil moisture data for irrigation timing and quantification, crucial for water resource monitoring, particularly in water scarce contexts. The availability of field-scale yield data for irrigated and rainfed fields will allow for direct comparison on the value added by irrigation for agricultural production, potentially incentivizing further irrigation-related investments.

Despite the limitations, we can demonstrate the efficacy of Earth Observation to monitor annual irrigation change in an inaccessible area, and as a result, give a base to broader analysis on land and water use in conflict zones.

5 Conclusion

This study introduces a transferable semi-supervised workflow combined with a rigorous sampling approach for area estimation, which can be rapidly deployed to map crop water usage in inaccessible or active conflict zones. Satellite Earth Observation has been a quintessential tool to monitor the impact of the full-scale invasion of Ukraine, particularly in the occupied regions. This study, which assessed the loss in irrigated area and the resulting change of crop types in Kherson and Zaporizhzhia oblasts following the loss of the Kakhovka Dam in 2023, contributes to the growing body of literature on the harm caused to Ukraine's agriculture. Area estimation using Earth Observation and sampling techniques show that the start of the full-scale invasion led to a partial loss of irrigation in 2022, followed by a dramatic decline in sufficient irrigation 2023, and a near total loss of irrigation in 2024 and 2025. Additionally, changes in crop types being planted (a shift from summer crops to winter crops) and abandonment have been documented. In the confluence of conflict, climate change, and food security, such investments in agricultural infrastructure will be key to building back Ukraine's capacity as the breadbasket of the world.

Data availability statement

Irrigated map products are available on Zenodo: <https://zenodo.org/records/22036773>.

Author contributions

SB: Project administration, Validation, Conceptualization, Data curation, Writing – review and editing, Methodology, Supervision, Writing – original draft, Investigation, Resources, Funding acquisition, Visualization, Software, Formal Analysis. SS: Formal Analysis, Methodology, Writing – review and editing, Conceptualization. YS: Conceptualization, Writing – review and editing, Methodology. LS: Methodology, Writing – review and editing. OO: Data curation, Writing – review and editing. MH: Writing – review and editing, Resources. JW: Writing – review and editing, Resources. AK: Writing – review and editing, Resources. SN: Resources, Writing – review and editing. AK: Writing – review and editing, Resources. IB-R: Conceptualization, Funding acquisition, Writing – review and editing.

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Conflict of interest

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Supplementary material

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/frsen.2026.1920951/full#supplementary-material>

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