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IMPROVEMENT OF METHODOLOGY FOR ASSESSING THE DYNAMICS OF DEGRADATION AND DIRECT ECONOMIC LOSSES OF THE AGRICULTURAL SECTOR IN THE CONDITIONS OF MODERN CHALLENGES CAUSED BY MILITARY ACTIONS

The object of research is the process of assessing the dynamics of degradation and direct economic losses of the agricultural sector. The hypothesis of research is based on the assumption that the regression model is able to provide a reliable short-term assessment (with a lag of 1 year) of the actual state of land use.

Improved methodology for assessing the dynamics of degradation and direct economic losses in the agricultural sector, which, unlike the known ones, involves the following stages:

– analysis of the dynamics of the Red and NIR channels within the study area to identify patterns of degradation of agrophytocenoses;
– determination of a statistical criterion of landscape structural order (OSI) to differentiate target crops from ruderal vegetation;
– conducting a linear regression analysis to determine the areas of active production based on the spectral characteristics of satellite data.

Experimental studies have been conducted to assess the volume of direct economic losses in the agricultural sector for the period 2022–2025. Analysis of the dynamics of spectral channels for 2016–2025 showed that starting from 2022, a "scissors" effect has been observed – a steady increase in the average in the Red channel and a decrease in NDVI, which is a sign of land withdrawal from cultivation. In the pre-war period, OSI values were in the range of 0.3–0.7, and starting from 2022 they became negative (about –1.5), which corresponds to the loss of structural integrity of the agricultural landscape. The calculated direct economic losses in the agricultural sector of the Kyiv region (Ukraine) for 2022–2025 are 491.7–548.11 million USD, depending on the calculation method. The gap between official statistics and the calculation method (37.26 million USD) corresponds to the crop that was sown but not harvested due to military threats.

Keywords: *dynamics of agricultural sector degradation, satellite data, vegetation indices, "scissors" effect, structural order index, direct economic losses.*

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1. Introduction

The 2022 aggression caused a systemic destabilization of the agro-industrial sector of Ukraine, which led to mass mining of territories, destruction of assets and disruption of technological cycles [1].

A specific consequence of the military actions was intensive secondary succession – filling of abandoned lands with ruderal vegetation [1]. More than 14,000 km² of arable land along the front line were left outside the limits of cultivation, which led to their rapid degradation [1]. This creates the effect of spectral mimicry, due to which traditional monitoring methods based on the vegetation index Normalized Difference Vegetation Index (*NDVI*) show incorrect data. Incorrect data relate to underestimation of active areas due to spectral anomalies (crates, burns) and their significant overestimation due to intensive weeding of abandoned fields [2]. Such statistical error makes it impossible to accurately predict the gross collection and distorts the assessment of economic losses.

Existing methods for assessing the dynamics of degradation and direct economic losses of the agricultural sector cannot be directly applied in the conditions of modern challenges caused by military actions. The optimal tool for assessing the dynamics of degradation and direct economic losses of the agricultural sector is the data of the Sentinel-2 satellite constellation [3, 4]. The use of remote sensing data of the Earth ensures efficiency, openness of data and the possibility of auditing

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dangerous areas without the need for ground surveys [5]. In addition, the availability of archives since 2015 allows for a retrospective comparison of the state of agricultural landscapes in the periods before and after the start of the active phase of the conflict [6, 7].

Therefore, the above indicates the relevance of improving the methodology for assessing the dynamics of degradation and direct economic losses of the agricultural sector in the conditions of modern challenges caused by military actions.

According to the World Bank and Kyiv School of Economics (KSE) Institute (2024), the total losses and damages of the industry as of the end of 2024 exceeded 80 billion USD, with more than 50% of these losses being related to the shortfall in the harvest of annual crops [8, 9].

In [10] it is stated that the methodology for assessing the dynamics of degradation and direct economic losses of the agricultural sector is necessary for [10]:

– identifying areas that have actually fallen out of the production cycle;
– prioritizing demining and restoration of the land fund;
– supporting the accuracy of global food security forecasts.

In [11] it is stated that the assessment of economic losses in agriculture from military conflicts is usually based on two approaches. The first is declarative, which is based on reporting by agricultural enterprises and government agencies. As KSE Institute experts note in their reports "Damage to Ukraine's Infrastructure", this method has significant drawbacks [12]:

– subjectivity of primary data;
– risk of duplication of requests;
– significant time lag, which is critical for areas with limited physical access.

The second is remote, where the key tool is the use of vegetation indices based on remote sensing data.

In [13], the normalized difference vegetation index (*NDVI*) was used to monitor food security. *NVDI* is used in the Group on Earth Observations Global Agricultural Monitoring (GEOGLAM) system. The disadvantage of [13] is that it does not take into account the conditions of military operations, since using only *NDVI* leads to erroneous results.

In [14], a method for classifying ruderal vegetation is proposed. In [14], ruderal vegetation is understood as agricultural fields overgrown with weeds. The disadvantage of the method [14] is the erroneous relationship of weeds to agricultural crops.

This disadvantage, noted in [14], was confirmed as a result of practical assessments of the consequences of regional military conflicts in Syria [15] and Ethiopia [16]. The method [14] does not take into account secondary succession. Therefore, it is necessary to introduce additional indicators for separating agricultural crops from weeds. This is the approach proposed in [17].

In [17], the use of the characteristics of the Red and Near-Infrared (NIR) spectral channels is prohibited. Analysis of the characteristics of these channels allowed monitoring of biomass. However, the method [17] does not take into account the peculiarities of military operations (for example, craters, mines, fortifications, etc.).

In [18], a method for estimating the spectral characteristics of soils and vegetation and determining vegetation indices based on this is proposed. The disadvantage of [18] is that it does not take into account the destruction of soils and vegetation.

In [19], a method for processing images from Sentinel space systems based on pixel-by-pixel analysis algorithms is proposed. However, this method does not take into account the heterogeneity of territories caused by the appearance of the so-called "war landscape" (Conflict Landscapes). Therefore, it is advisable to introduce a method that takes into account orientation to certain objects in the images. This is what is proposed in [20].

In [20], a method for processing images from Sentinel space systems is developed, taking into account objects of interest in the image. However, the method [20] does not take into account the conditions of military operations, which leads to the loss of the geometry of objects of interest and leads to a violation of the orderliness of agrocenoses.

In [21], machine learning methods are proposed for analyzing Sentinel-2 satellite data. Methods [21] were used to predict crop yields and classify crops. However, methods [21] are ineffective in the languages of military operations.

In [22], a machine learning method was developed to analyze the state of agricultural fields. The disadvantage of [22] is the inconsistency of training samples with the real state of agricultural fields.

In [23], a method was developed that takes into account spatial parameters in regression models. This allowed to reduce the error in estimating productivity losses. The disadvantage of [23] is that the impact of military operations is not taken into account.

In [24], an additional indicator was proposed – the structural order index. Such an index takes into account weighting factors in estimating economic losses. The disadvantage of [24] is that the impact of military operations is not taken into account.

In [25], a method was proposed to estimate the dynamics of land degradation. However, the methods of [25] are more focused on the analysis of the state of protected areas and cannot be directly applied to the analysis of the degradation of the agricultural sector.

In [26], methods combining machine learning and statistical regression are proposed for the assessment of agricultural losses. The disadvantages of [26] are the complexity of obtaining training samples and their inconsistency with the state of agricultural fields.

In [27], a method using machine learning models is proposed to isolate the impact of conflict on agricultural lands. However, the method does not take into account the impact of military actions on climate change and does not ensure the stability and sustainability of agricultural systems.

In [28], recurrent neural network models are proposed. Such models are able to capture spatial and temporal features from time series data and sequential data. The disadvantage of the method is that it is forecasting for a short period of time and does not take into account the impact of military actions.

In [29], an assessment of the impact of natural disasters on the agricultural sector is proposed. The analysis was conducted for low- and middle-income countries. Therefore, the results cannot be used in the analysis of the agricultural sector in other conditions.

In [30], a methodology for assessing damage to land and soil as a result of armed aggression and hostilities is proposed. However, the methodology does not take into account certain indicators that allow separating agricultural crops from weedy (ruderal) vegetation.

Thus, the analysis [8–30] indicates the following:

– existing methods for assessing the dynamics of degradation and direct economic losses in the agricultural sector do not take into account the conditions of modern challenges caused by military actions;
– there is no single method that would integrate the spectral analysis of the dynamics of the Red/NIR channels with the mathematical assessment of structural degradation of the landscape;
– there are significant errors in determining real economic losses, in particular due to the inability to accurately separate commercial crops from degraded areas;
– a criterion has not been developed that would allow differentiating target crops from ruderal vegetation and converting these data into a cost estimate of losses;
– the area of lost land is not verified.

All this gives grounds to argue that it is advisable to conduct a study on improving the methodology for assessing the dynamics of degradation and direct economic losses of the agricultural sector in the conditions of modern challenges caused by military actions.

The object of research is the process of assessing the dynamics of degradation and direct economic losses of the agricultural sector in the conditions of modern challenges caused by military actions. The process of assessing the dynamics of degradation and direct economic losses of the agricultural sector was carried out using the example of the transformation of agricultural landscapes of the Kyiv region (Ukraine) under the influence of military actions. The choice of the region is due to a combination of destabilizing factors: mechanical damage to soils, weediness of land and limited physical access for ground data verification [31].

The aim of research is to improve the methodology for assessing the dynamics of degradation and direct economic losses of the agricultural sector in the conditions of military impact based on remote sensing data.

The hypothesis of research is based on the assumption that the regression model is able to provide a reliable short-term assessment (with a lag of 1 year) of the actual state of land use. The use of such a model will allow for an independent audit of active production areas and verification of official statistical data under conditions of high uncertainty [32, 33].

To achieve the aim, the following objectives have been defined:

1. To present the main stages of an improved methodology for assessing the dynamics of degradation and direct economic losses in the agricultural sector.

2. To conduct an experimental study on the testing of an improved methodology for assessing the dynamics of degradation and direct economic losses in the agricultural sector by assessing the volume of direct economic losses in the agricultural sector for the period 2022–2025.

2. Materials and Methods

The following assumptions were made in the research:
- the regression model is trained on combined time series (including both stable periods 2016–2021 and crisis periods 2022–2025);
- the model requires constant updating (retraining) based on current data from the war period to take into account new vegetation anomalies;
- the predictive ability of the model is limited to one vegetation cycle, which is due to the dynamics of war and agro-climatic factors [32–35];
- the input data are time series of Sentinel-2 (Level-2A) images for 2016–2025;
- the spatial resolution of Sentinel-2 (Level-2A) images is 10–20 m;
- Sentinel-2 (Level-2A) image series for 2016–2025 were obtained through the Copernicus Data Space Ecosystem platform [6];
- spectral channels B04 (Red) and B08 (NIR) were used for the analysis, the values of which were normalized to the range [0, 1];
- normalization of spectral channels B04 (Red) and B08 (NIR) to the range [0, 1] was carried out according to the standards of atmospheric correction reprocessing;
- brightness distributions for the Red and NIR channels are bimodal.

The following research methods were used:
- digital image processing;
- neural networks;
- regression analysis;
- series theory;
- comparative analysis;
- probability theory and mathematical statistics;
- optimization theory;
- empirical research;
- mathematical modeling.

The research methods were selected taking into account the formulated research objectives.

When determining the main stages of the improved methodology for assessing the dynamics of degradation and direct economic losses of the agricultural sector, the following theoretical methods were used:
- digital image processing;
- neural networks;
- regression analysis;
- series theory;
- probability theory and mathematical statistics;
- optimization theory.

The choice of the above theoretical research methods is due to:
- analysis of the dynamics of the Red and NIR channels within the study area to identify patterns of degradation of agrophytocenoses;
- determination of the statistical criterion of the structural order of the landscape (Orderliness Structure Index (*OSI*)) to differentiate target crops from ruderal vegetation;
- conducting linear regression analysis to determine the areas of active production based on the spectral characteristics of satellite data.

When conducting an experimental study on the testing of an improved methodology for assessing the dynamics of degradation and direct economic losses in the agricultural sector, the following theoretical and practical research methods were used:
- empirical research;
- mathematical modeling;
- probability theory and mathematical statistics;
- regression analysis;
- comparative research.

The choice of the above theoretical and practical research methods is due to:
- conducting an experiment on an improved methodology using real data;
- conducting regression analysis based on satellite data;
- assessing the dynamics of degradation and direct economic losses in the agricultural sector.

Used:
- *hardware:* Dell laptop Intel® Core™ i7–8650U CPU@ 1.90 GHz;
- *software:* object-oriented programming language Python 3.11, programming language Matlab 7 with a package of application programs.

3. Results and Discussion

3.1. Main stages of the improved assessment methodology

The main stages of the improved methodology for assessing the dynamics of degradation and direct economic losses of the agricultural sector are:
- analysis of the dynamics of the Red and NIR channels within the study area to identify patterns of degradation of agrophytocenoses;
- determination of the statistical criterion of the structural order of the landscape (Orderliness Structure Index (*OSI*)) to differentiate target crops from ruderal vegetation;
- conducting linear regression analysis to determine the areas of active production based on the spectral characteristics of satellite data, using the actual yield as a control indicator.

When analyzing the dynamics of the Red and NIR channels within the study area, the vegetation index $NDVI(x, y)$ is calculated for each pixel by

$$NDVI(x,y)=\frac{NIR(x,y)-Red(x,y)}{NIR(x,y)+Red(x,y)}, \quad (1)$$

where $NIR(x, y)$ and $Red(x, y)$ – the reflectance values in the corresponding channels; (x, y) – the coordinates of the pixel in the image.

At the same time, $NDVI(x, y)$ by construction takes values in the range [–1, 1], but negative values are not taken into account. Such values usually correspond to water bodies or snow cover and are not informative for agromonitoring tasks [25].

Time series processing included the formation of cloudless composites to eliminate atmospheric interference. The statistical basis for training and verification of the models was the data of the State Statistics

Service [32, 35], reports of the Kyiv Regional State Administration [33] and agrometeorological bulletins of the UkrHydrometcenter [34]. The use of these sources allowed comparing remote indicators with official data on crop areas and yields in the Kyiv region during 2024–2025.

To objectively identify areas of loss of anthropogenic control, the Orderliness Structure Index (*OSI*) was introduced in the work. This indicator is a statistically normalized metric that characterizes the degree of spatial and spectral homogeneity (homogeneity) of the vegetation cover.

The physical and informational feasibility of implementing *OSI* is based on differences in the topological structure of the studied objects, namely:

– cultural agrocenoses form spatially determined structures with low spatial variability of spectral features, which gives a high signal/noise ratio;

– ruderal vegetation (wild grasses, weeds), despite the ability to generate an intensive vegetation response (*NDVI*), is characterized by a high level of spatial entropy, fragmentation, and spectral noise.

The calculation of the introduced *OSI* indicator is based on a comparison of the relative stability of the vegetation index and the basic spectral channels NIR and Red. OSI is defined as the difference between the coefficient of variation of the *NDVI* and the average coefficient of variation of the spectral channels NIR and Red

$$\text{OSI}=\frac{\mu_{NDVI}}{\sigma_{NDVI}}-\frac{1}{2}\left(\frac{\mu_{NIR}}{\sigma_{NIR}}+\frac{\mu_{Red}}{\sigma_{Red}}\right), \quad (2)$$

where $\mu_{NDVI}, \mu_{NIR}, \mu_{Red}$ – the mathematical expectations of the corresponding values within the area of interest; $\sigma_{NDVI}, \sigma_{NIR}, \sigma_{Red}$ – their standard deviations.

For adaptive area estimation, a multiple linear regression model is built that approximates the relationship between the spectral characteristics of the landscape and the areas of active land use.

The implementation algorithm consists of the following steps:

1. For each annual cycle, a feature vector *xi* is formed, which includes mathematical expectations μ, standard deviations σ, and the values of adaptive *Otsu* segmentation thresholds τ for the *Red* and *NIR* spectral channels. It is assumed that the brightness distributions for these channels are bimodal, therefore, the use of thresholds τ allows to track the boundary between vegetation and open ground [36, 37].

2. The target variable is the known area of vegetation.

3. The linear regression model is given

$$y_{pred}=\beta_0+\sum_{i=1}^{n}(\beta_i x_i)+\varepsilon, \quad (3)$$

where βi – calculated regression coefficients; xi – spectral features; ε – model error.

4. The model is initialized on retrospective data (2016–2021) and is sequentially trained by including data from the war period (2022–2025). The short-term (1 year) nature of the model is due to the need to calculate the β coefficients for each new vegetation cycle.

Thus, the improved methodology for assessing the dynamics of degradation and direct economic losses of the agricultural sector, unlike the known ones, involves:

– analysis of the dynamics of the Red and NIR channels within the study area to identify patterns of degradation of agrophytocenoses;

– determination of a statistical criterion of landscape structural order (*OSI*) for differentiating target crops from ruderal vegetation;

– conducting linear regression analysis to determine active production areas based on spectral characteristics of satellite data, using actual yield as a reference indicator.

3.2. Experimental studies on the testing of the improved assessment methodology

To verify the developed methodology, a comprehensive monitoring of agricultural landscapes of the Kyiv region was conducted. Analysis of the time series of the calculated vegetation index *NDVI* for the period 2016–2025 allows to clearly see the transition from the pre-war period (2016–2021) to the time of the military conflict (2022–2025) (Fig. 1).

From the analysis of Fig. 1 it is clear that in the pre-war period (2016–2021) the agricultural landscapes of the studied region were characterized by high orderliness. This period was marked by a gradual intensification of land use, which was reflected in a steady increase in *NDVI* values in the phase of maximum vegetation.

The anomaly of 2019, which is reflected as a uniform decrease in the vegetation index throughout the region, is explained by a deficit of precipitation. According to the UkrHydromet Center, 2019 was one of the driest in the history of observations. It should be noted that, unlike military transformations, the climatic anomaly of 2019 was homogeneous in nature, since the structure of the fields remained unchanged. This confirms the ability of the model to distinguish natural stresses from military destruction.

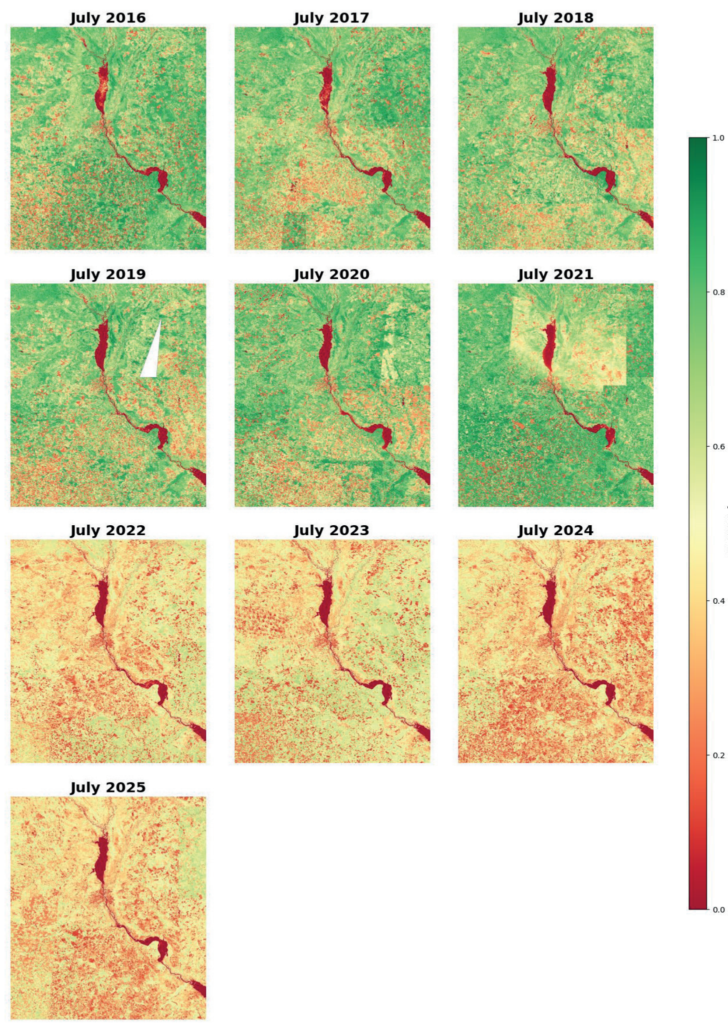

Fig. 1. Distribution of the Normalized Difference Vegetation Index (*NDVI*) during the peak growing season (2016–2025)

Starting from 2022, a sharp drop in *NDVI* values to levels of 0.2–0.4 is visible, which indicates a violation of agrotechnological cycles.

To confirm the degradation of agrophytocenoses, graphs of spectral reflectance in the NIR and Red channels and *NDVI* were constructed (Fig. 2). From the analysis of Fig. 2, it can be seen that, starting from 2022, the effect of convergence of channels is recorded, which visually creates a "scissors" effect, namely:

– the average in the Red channel is growing, which indicates a transition from homogeneous crops to fragmented wild communities;

– the average in *NDVI* is falling, which indicates a decrease in chlorophyll concentration and, accordingly, crop degradation.

The convergence of the values of these channels indicates that the fields have left agricultural circulation.

For quantitative assessment of the quality of the agrolandscape, the introduced structural order index (*OSI*) was tested. The calculation of the indicator was carried out according to expression (2) based on Sentinel-2 data for the peak vegetation period (July–August) 2016–2025. The calculation results are shown in Fig. 3.

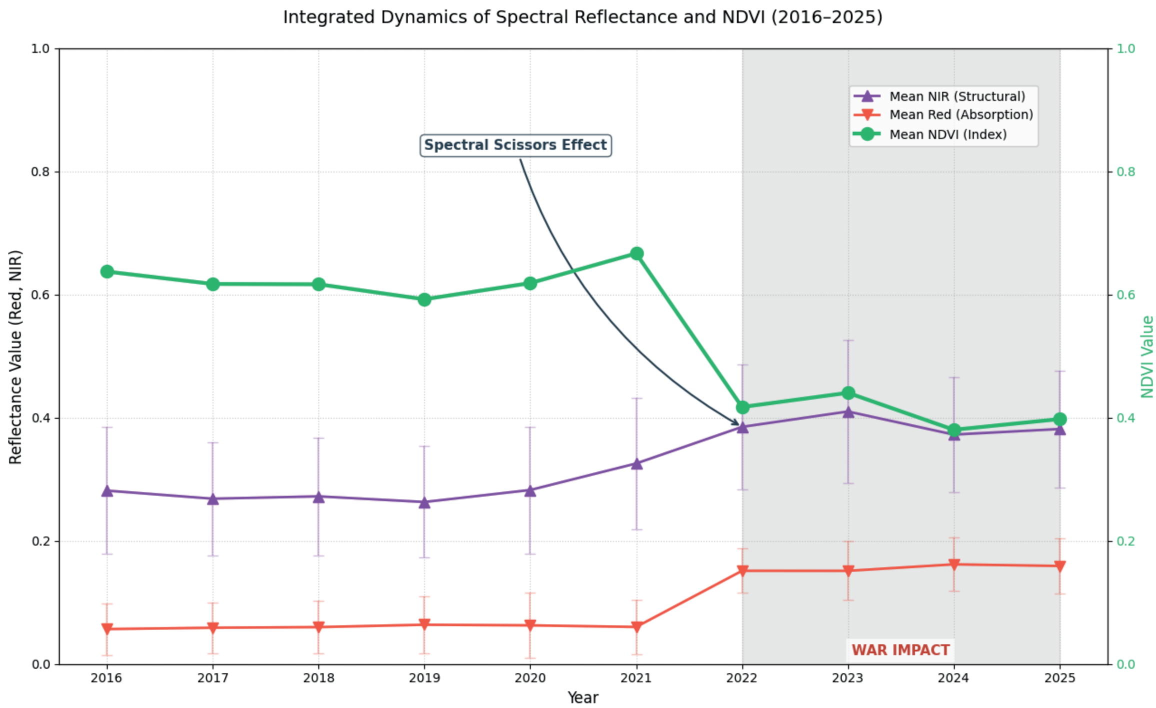

Fig. 2. Integrated dynamics of spectral reflectance in near-infrared (*NIR*), Red bands, and the Normalized Difference Vegetation Index (*NDVI*) during 2016–2025: the arrow indicates the "spectral scissors" effect; the grey shaded area represents the period of military conflict

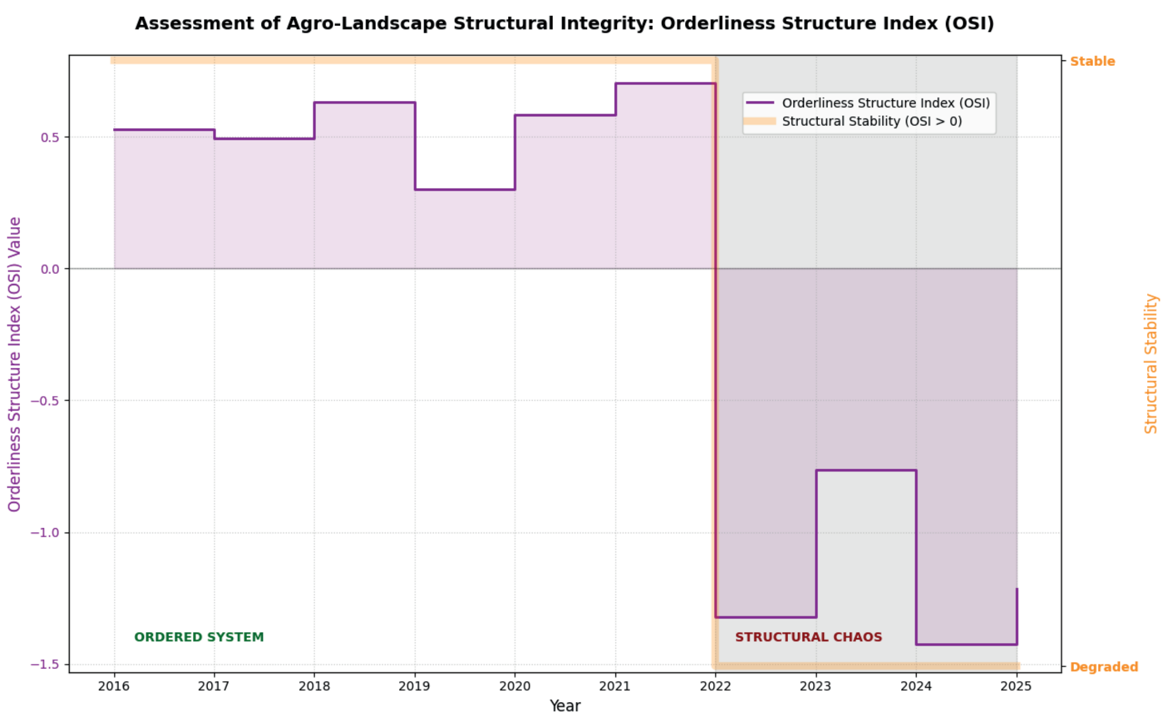

Fig. 3. Assessment of agricultural landscape quality based on the proposed Orderliness Structure Index (*OSI*) during the peak growing season (July–August, 2016–2025): left axis – *OSI* values; right axis – share of degraded lands, %

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Analysis of *OSI* dynamics (Fig. 3) allows to identify three phase states of the studied system:

1. *Stable order phase (2016–2021).* The *OSI* value takes on positive values (0.3–0.7), which corresponds to the structural stability regime.

2. *Point of change (2022).* The *OSI* value coincides with the beginning of intensive military influence, *OSI* changes sign, which means the loss of structural integrity of the agricultural landscape.

3. *Stage of structural chaos (2022–2025).* The *OSI* value becomes negative (at the level of about –1.5), which means the transition to a state of degradation.

To estimate the area of active land use, a regression model based on a multidimensional feature vector was used. A set of predictors was formed for each annual cycle (2016–2025). The set of predictors includes, as mentioned above, the mean values (μRed, μ_{NIR}), the root mean square deviations (σRed, σNIR) and the Ott segmentation threshold values (τRed, τNIR) for the corresponding spectral channels. The analysis of the importance of the features showed that the greatest contribution to the model prediction is made by the τRed and τNIR indicators, as shown in Fig. 4. This fact confirms the role of segmentation thresholds in the separation of target crops and degraded areas.

To verify the objectivity of the monitoring, the following indicators were compared (Table 1):

1. *Official crop area:* reflects the declared land use volumes (baseline for 2016–2021).

2. *Estimated harvest area:* determined by the ratio of gross harvest to average yield. This is a priority benchmark for the war period, as it is based on the real biomass yield and allows verifying the ability to ignore sown but not harvested or degraded areas.

3. *Model forecast:* the result of the improved methodology based on satellite data (remote sensing data).

The improved method showed $R^2 = 0.88$ (where R^2 – the Pearson criterion) with a Mean Absolute Percentage Error (*MAPE*) of *MAPE* = 1.35% (Fig. 5).

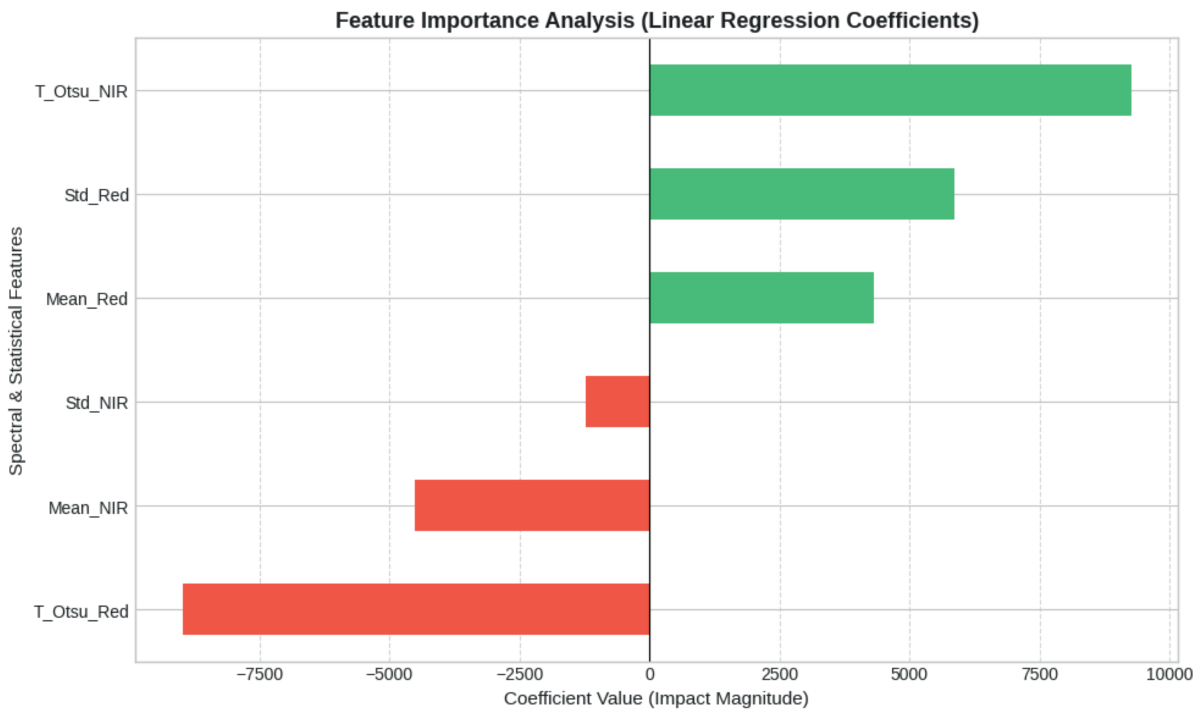
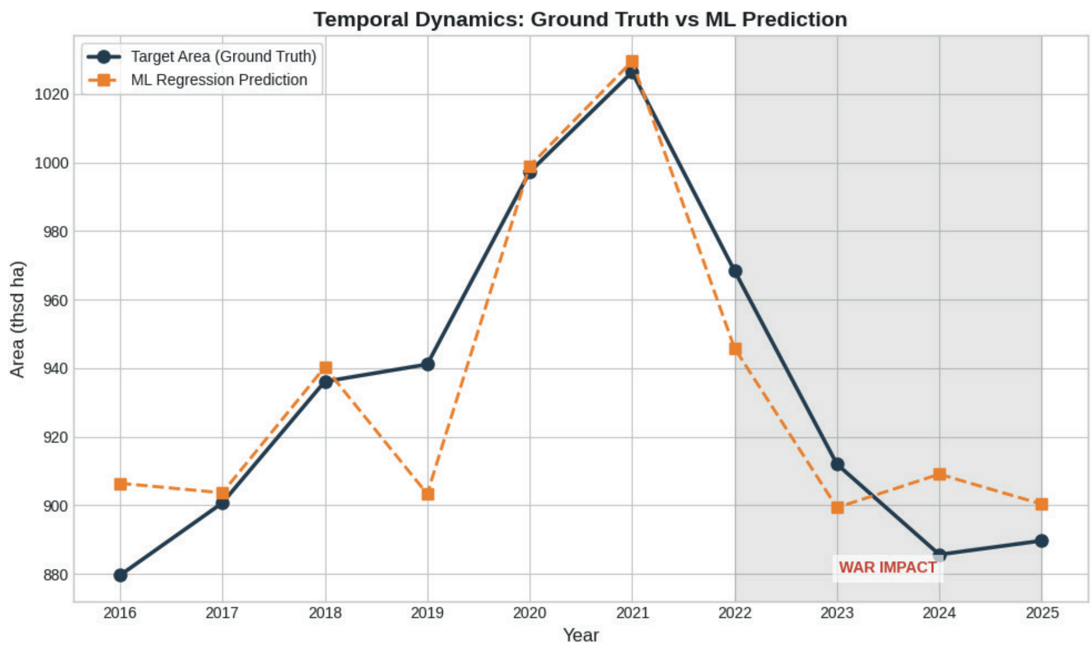


Fig. 4. Feature importance analysis of parameters in the regression model for estimating agricultural landscape transformation areas: relative contribution of vegetation indices and spectral bands to the overall model accuracy

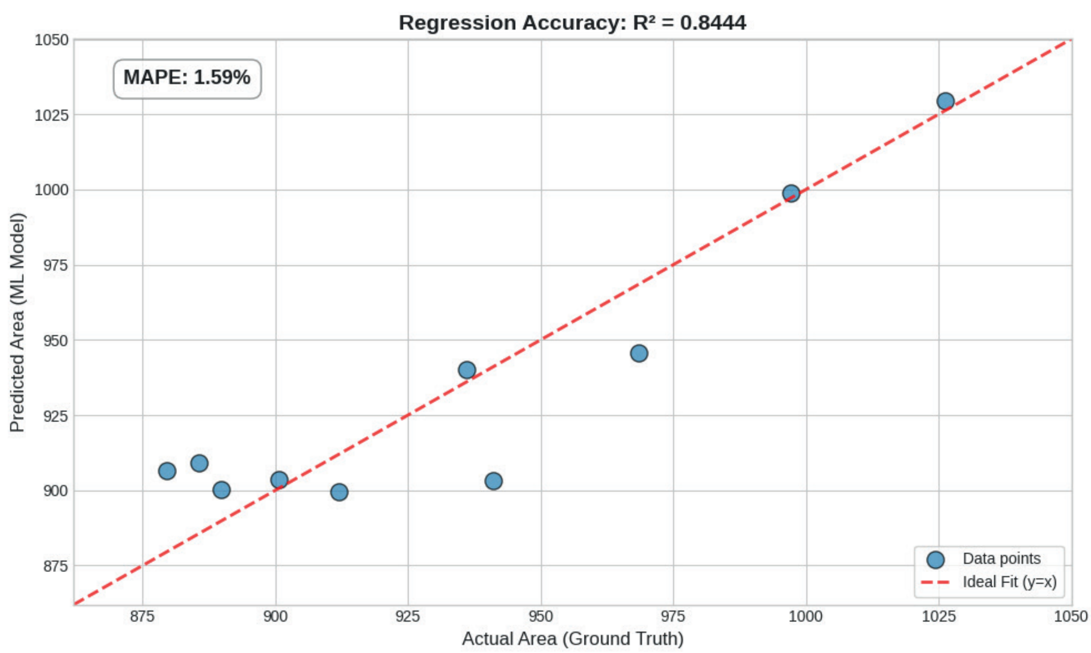
Table 1

Verification of modeling results and comparison with reference indicators (thousands of hectares)

Year	Sown area	Calculated area	Model forecast	Model deviation (%)
2016	879.60	876.03	906.44	+3.47
2017	900.70	889.92	903.65	+1.54
2018	936.10	932.90	940.30	+0.79
2019	941.10	935.26	903.33	–3.41
2020	997.20	989.99	998.93	+0.90
2021	1026.30	1022.12	1029.47	+0.72
2022	968.40	943.68	945.85	+0.23
2023	912.00	908.42	899.35	–1.00
2024	885.65	883.19	909.09	+2.93
2025	889.70	889.75	900.35	+1.19



a



b

Fig. 5. Accuracy assessment of the regression model for estimating active land-use areas: *a* – time-series dynamics of the model prediction relative to the reference indicator; *b* – "predicted vs. actual" scatter plot with a line of ideal approximation (regression line $Y = X$)

To assess the quality of the improved methodology, an assessment of the lost profit of the agricultural sector was carried out. This assessment is based on the calculation of the deficit of sown areas relative to the established baseline level for assessing the value of the uncollected harvest.

The baseline value is the level of areas $S_{base,}$ as the average value for the last three pre-war years (2019–2021)

$$S_{base} = \frac{1}{3}\left(S_{2019} + S_{2020} + S_{2021}\right). \tag{4}$$

This approach is consistent with international standards for damage assessment (Post-Disaster Needs Assessment (PDNA)). where the average indicators before the conflict are taken as the basis.

The reduction in active land use areas $\Delta Sloss$ is defined as the non-negative difference between the baseline $Sbase$ and the actual $Sfact$ indicators

$$\Delta S_{loss} = \left(S_{base} - S_{fact}\right)_{+}. \tag{5}$$

The total amount of lost profit is calculated as the sum of losses by main groups of agricultural crops

$$L_{total} = \sum_i \left(\Delta S_{loss} k_i Y_i P_i\right), \tag{6}$$

where ki – the share of the i-th crop in the crop structure; Yi – the average yield; Pi – the market price of a unit of production.

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Table 2 presents the results of the assessment of direct economic losses in Kyiv region caused by changes in agricultural landscapes. The calculation of the deficit of active areas and the corresponding losses was carried out for official area values, for estimated values based on yield and using an improved methodology based on satellite data (Table 2).

Table 2

Comparative assessment of cumulative economic losses in the agricultural sector of Kyiv region (millions USD)

Year	Losses according to statistical data (sown areas)	Calculated losses (by yield)	Losses according to regression model (satellite data)
2022	22.4	50.29	47.88
2023	108.80	113.84	126.96
2024	181.26	185.7	139.89
2025	198.4	198.28	176.97
TOTAL	510.86	548.11	491.7

Analysis of Table 2 shows the following:

1. Total direct losses of the agricultural sector of the region for the period 2022–2025 range from 491.7 to 548.11 million USD. Visualization of the deficit of areas compared to the pre-war baseline (Baseline) is shown in Fig. 6. The highest loss indicator (548.11 million USD), recorded by the calculation method, indicates a significant "invisible" deficit of production in the territories that were formally considered sown, but were not actually harvested due to military threats.

2. The machine learning model showed consistency with official reporting of 96.2%. The accuracy of identifying real production relative to the yield standard reaches 89.7%, which confirms the suitability of the model for assessing losses.

3. The maximum deviation between the forecast using the improved methodology and official data did not exceed 19.43 million USD. At the same time, the identified gap between statistical and estimated data (37.26 million USD) confirms the feasibility of using multi-level verification to identify the real crop shortfall.

4. Comparison of financial indicators with the dynamics of the structural order index (*OSI*) (Fig. 7) shows that the peak values of losses correspond to OSI drops to –1.25 in 2022 and –1.20 in 2025.

Analysis of Table 2, Fig. 6 and Fig. 7 confirms that the economic depletion of the industry is a consequence of the chaos and fragmentation of the agricultural landscape.

The use of linear regression based on satellite data allows to find a good estimate of land use areas in zones of military conflict. The results obtained confirm that direct monitoring of vegetation allows to determine the real state of land use regardless of administrative factors. This is important for forming an evidence base when assessing losses in deoccupied territories, where access to fields may be limited due to mine danger.

The relationship between the OSI index and economic losses is explained by changes in technological processes. The transition of the index to negative values indicates the destruction of the integrity of the agricultural landscape. Field fragmentation (the appearance of funnel zones, trenches, unharvested areas) leads to an increase in logistical costs and reduces overall labor productivity.

Therefore, the OSI indicator introduced in the work can be an indicator of the efficiency of agribusiness in crisis conditions.

The difference between the declared areas and the actual harvest (37.26 million USD) indicates systemic risks that are not recorded by conventional crop statistics. This confirms that in war conditions, the fact of "sowing" does not guarantee "harvesting". The satellite model identifies areas where vegetation occurred, but the crop was not harvested or was destroyed before harvest.

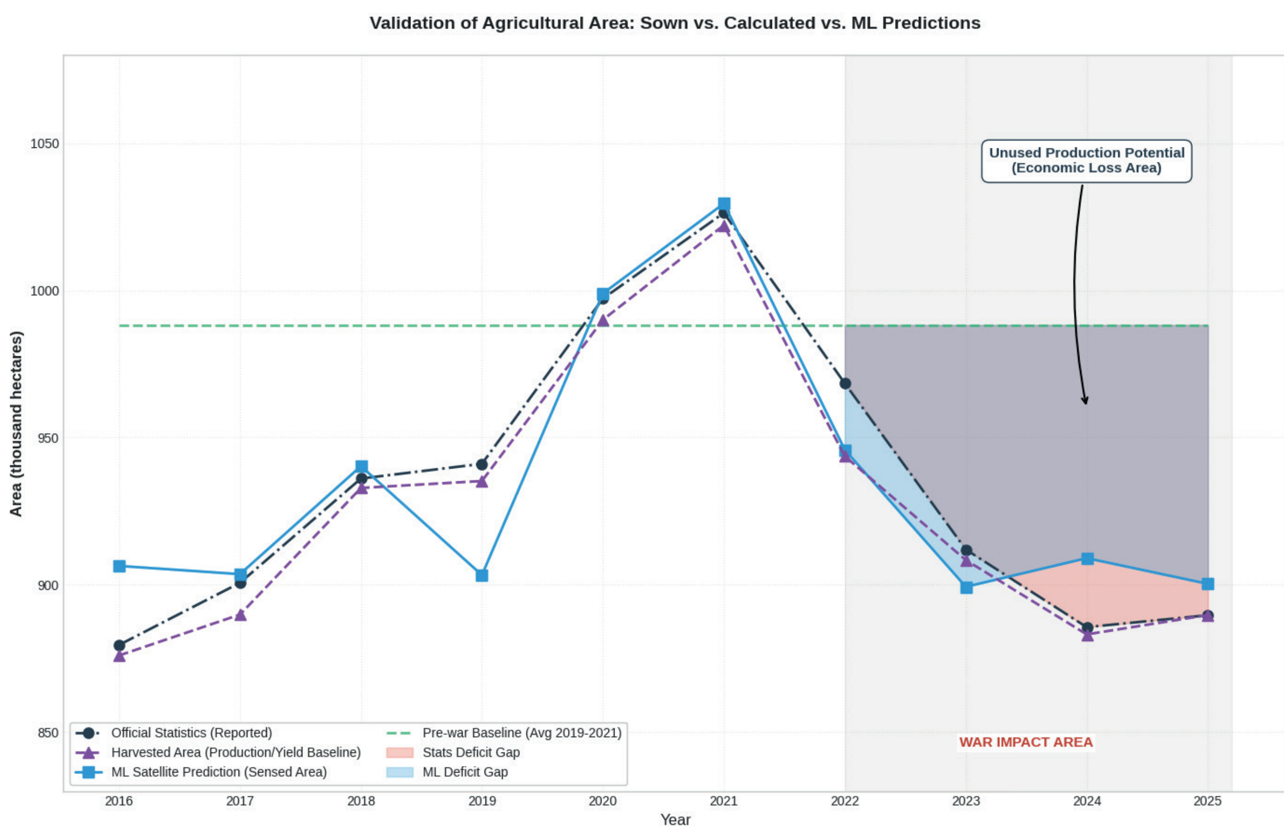

Fig. 6. Comparative dynamics of areas according to official statistics, calculations based on crop yields, and regression model forecast: area deficits for official and model data are shown (the grey shaded area represents the period of military conflict)

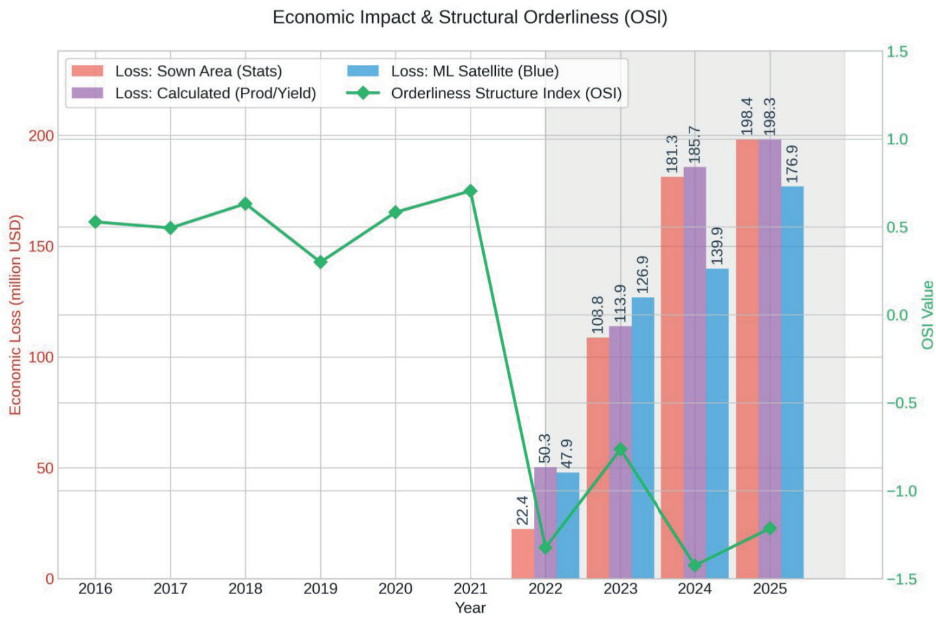

Fig. 7. Comprehensive analysis of economic impact and structural degradation of agricultural landscapes: histograms display estimated economic losses (million USD) based on three data sources; the line chart shows the dynamics of the Orderliness Structure Index (*OSI*)

The loss assessment has an error due to the volatility of prices on the grain market and changes in exchange rates in the period 2022–2025. It is also necessary to take into account the spectral similarity of weeded lands to crops of some crops at the initial stages of growth, which may lead to an overestimation of active areas in the model. However, the estimates obtained are conservative and statistically reliable.

The proposed approach should be used to model the order of land restoration. The priority of demining and reclamation should be determined not only by the area of the site, but also by its ability to restore the structural order (*OSI*) of the agricultural landscape.

The improved methodology for assessing the dynamics of degradation and direct economic losses of the agricultural sector can be used to assess the agricultural sector, determine the priority of demining and reclamation of any territory in the context of military operations.

3.3. Limitations and prospects for research development

The limitations of the research are:
– the methodology is improved only for the agricultural sector and does not apply to other sectors;
– limitations of input data for analysis (only a series of Sentinel-2 (Level-2A) images for 2016–2025);
– limitations of the model's predictive ability to one vegetation cycle;
– the methodology is improved for assessing direct economic losses, other losses are not considered;
– the methodology has been tested in conditions of challenges caused only by military operations.

The prospects for further research are:
– conducting an experimental study to assess the dynamics of degradation and direct economic losses of the agricultural sector in other territories, for example, temporarily occupied territories of Ukraine;
– determining and evaluating other quality indicators of the adaptive agromonitoring methodology.

4. Conclusions

1. Improved methodology for assessing the dynamics of degradation and direct economic losses of the agricultural sector, which, unlike the known ones, involves the following stages:
– analysis of the dynamics of the Red and NIR channels within the study area to identify patterns of degradation of agrophytocenoses;
– determination of a statistical criterion for the structural order of the landscape (*OSI*) to differentiate target crops from ruderal vegetation;
– conducting linear regression analysis to determine the areas of active production based on the spectral characteristics of satellite data, using actual yield as a control indicator.

2. Experimental studies were conducted to test an improved methodology for assessing the dynamics of degradation and direct economic losses in the agricultural sector by assessing the volume of direct economic losses in the agricultural sector for the period 2022–2025. Analysis of the dynamics of spectral channels for 2016–2025 showed that starting in 2022, a "scissors" effect has been observed – a steady increase in the average in the Red channel and a decrease in *NDVI*, which is a sign of land withdrawal from cultivation. The introduced *OSI* structural order index allows to distinguish active crops from secondary vegetation. In the pre-war period, *OSI* values were in the range of 0.3–0.7, and starting in 2022, they became negative (about –1.5), which corresponds to the loss of structural integrity of the agricultural landscape. The constructed regression model based on spectral features according to Sentinel-2 data showed R^2 = 0.88 and *MAPE* = 1.35%, which confirms its suitability for assessing the areas of active agricultural production in conditions of military conflict. The calculated direct economic losses of the agricultural sector of the Kyiv region for 2022–2025 are 491.7–548.11 million USD, depending on the calculation method. The gap between official statistics and the calculation method (37.26 million USD) corresponds to the crop that was sown but not harvested due to military threats.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

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The research was performed without financial support.

Data availability

Data will be made available on reasonable request.

Use of artificial intelligence

The authors declare the use of artificial intelligence technologies (LLM Gemini) during the preparation of this work in the following aspects:

– checking grammar, spelling, punctuation without changing the text;

– improving the original code created by the authors;

– visualizing the original author's data in the form of figures, graphs, diagrams or tables.

The authors confirm that artificial intelligence technologies were not used to generate, manipulate or supplement the original research data. All digital indicators, calculation results, diagrams and graphs are based exclusively on the original factual data obtained by the authors as a result of processing satellite images and official statistics.

Authors' contributions

Mykola Butko: Conceptualization, Methodology, Formal analysis, Writing – review and editing; ***Ihor Butko:*** Data curation, Formal analysis, Validation; ***Oleksandr Makoveichuk:*** Software, Visualization, Investigation, Resources, Writing – original draft; ***Vladislav Tiutiunnyk:*** Investigation, Data curation, Investigation, Resources; ***Hennadii Khudov:*** Visualization, Investigation, Writing – review and editing.

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