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RESEARCH OF FOOD SECURITY PROBLEMS OF THE WAR-TORN REGIONS OF UKRAINE USING GEOMATICS METHODS

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Abstract. Every year, the world faces new difficult challenges in maintaining global security. Compliance with food security principles is an important component of the global context of world development. Recent military conflicts have had a strong impact on the development of regions that provide food for millions of people around the world. Ukraine plays a key role in providing agricultural products to the population of countries from different continents. The article is devoted to the study of the state of agricultural crops in a regional section during the period of active hostilities by means of geomatics, which allow one to assess the degree of transformation of sustainable farming quickly, determine the trend of the development of the industry, and calculate the likely scale of changes in the obtained products in the coming years. As a result, with the help of deep learning models integrated into geoinformation systems, the boundaries of agricultural fields in the Kherson and Zaporizhia regions were determined, the state of moisture and bioproductivity of agricultural crops was determined for three years, an analysis of changes has been made in the state of agricultural fields under the influence of new factors of conducting active hostilities during the first half of 2022, the next harvest productivity forecast was made in two southern regions of Ukraine. The study was carried out by the team of the World Data Center for Geoinformatics and Sustainable Development of the Igor Sikorsky Kyiv Polytechnic Institute. It was part of research on the analysis of the behavior of complex socio-economic systems and processes of sustainable development in the context of the quality and safety of people's lives.

Keywords: food security, spatial data analysis, deep learning, agricultural fields, mathematical modeling.

INTRODUCTION

Intensification of extreme weather conditions, climate change processes, coronavirus pandemic, etc. led to an aggravation of the food situation for many countries of the world [1]. Before Russia`s full-scale invasion of Ukraine, the world was close to a global food crisis, but since February 24, 2022, the situation has significantly worsened [2]. Ukraine is a supplier of a large number of agricultural products to dozens of taps in the world. Ukraine has 15% of the global product market (UBTA) for individual grain crops [3]. Some countries of the world depend on certain types of agricultural products from Ukraine for more than 50%. The full-scale war led to a significant reduction in the area of cultivated agricultural areas, a decrease in the number of people and equipment involved in the cultivation of agricultural crops. In addition, the structure of management in the field of irrigation was transformed.

Combat actions and specific management decisions in the temporarily occupied territories have significantly changed the irrigation system that has existed for many years. The canal systems, which were fed from the Dnieper and transported water hundreds of kilometers to the south and east of the country, are under temporary occupation and their state of functioning is difficult to investigate. At the same time, the region continues to be a supplier of a significant amount of agricultural products, so it is extremely important to understand the degree of transformation processes in order to assess possible losses and predict the degree of the food crisis. Due to constant military operations, direct access to the territory is extremely difficult, reliable statistical data on the volume and condition of the harvest, irrigation of the territory, etc. are not collected, the only possible methods of assessing the degree of transformation of agricultural fields are methods of remote sensing of the Earth, and geomatics in general. The most characteristic signs of the transformation of the water regime, especially for irrigated areas, are signs of a sharp change in indicators of bioproductivity and territory moisture. Such characteristics can be obtained with high accuracy based on the analysis of satellite images of medium resolution, which is not a limiting factor based on the realities of war.

This study is a continuation of the thematic research of the team of authors on the study of sustainable development of communities and territories of Ukraine and security processes in the regions of the state [4, 5] and research on the development of the applications of geomatics methods [6, 7].

DATA FRAMEWORK

Two southern regions of Ukraine: Kherson and Zaporizhzhya, were chosen to assess the impact of the processes associated with the occupation on the condition of agricultural plots (Fig. 1).

Fig. 1. The study area (black borders) with the indicated averaged zones of temporary occupation as of May 2022 (gray color)

For most of the first four months of the active phase of the war, these areas have been partially occupied, and this period completely coincides with the period of active agricultural work, in particular with the irrigation of the territory. Remote monitoring of the state of moisture in agricultural fields, analysis of the distribution of the Normalized Difference Moisture Index (NDMI) on the territory, its dynamics over different years will allow to assess the degree of changes in sustainable agricultural practices in the region and assess the state of the potential harvest, which in the pre-war period for years provided food for the population of Ukraine and residents of countries that import agricultural products. The selected areas have a high share of plowed territory, both irrigated and non-irrigated agricultural fields, and a dense and fairly even distribution of plots throughout the territory. This makes it possible to distinguish the anthropogenic influence of the occupation itself on the situation with the moisture of agricultural fields from the general background climatic influence. The condition of plots exclusively on traditionally irrigated lands can be analyzed separately. In addition to the analysis of the differentiation of the moisture index, it is necessary to investigate the change in the bioproductivity index: Normalized Difference Vegetation Index (NDVI), which on the one hand directly correlates with the moisture content of the territory, but allows to distinguish the vegetation state of the vegetation itself, which affects the indices of the moisture index itself (there may be weakly moistened territories, however, due to the high vegetation, give the moisture index high values). The condition of plots exclusively on traditionally irrigated lands can be analyzed separately. In addition to the analysis of the differentiation of the moisture index, it is necessary to investigate the change in the bio productivity index: NDVI, which on the one hand directly correlates with the moisture content of the territory, but allows to distinguish the vegetation state of the vegetation itself, which affects the indices of the moisture index itself (there may be weakly moistened territories, however, due to the high vegetation, it gives the moisture index of high values).

To assess the impact of the occupation, mainly data from remote sensing of the Earth (DSR) [8], data on the administrative and territorial structure of the country [9] and the borders of temporarily occupied territories from open online sources [10] were used. For the analysis of moisture and bio productivity, data were obtained from the Sentinel-2 mission satellite, platforms 2-A and 2-B and product type S2MSI1C with a cloud cover of no more than 10% in the study area [11]. The resolution of multispectral three-channel images is 10 m per pixel, single-channel 20 m per pixel. Channels B08 and B11, bio productivity index: B08 and B04 were used to calculate the moisture index.

$$NDMI = (B08 - B11)/(B08 + B11); \quad (1)$$

$$NDVI = (B08 - B04)/(B08 + B04). \quad (2)$$

Data on the boundaries of regions, districts and communities of the study area were obtained from the official website of the support for the decentralization reform [12].

The boundary of the line of contact of the troops is dynamic and has not yet been determined, therefore the boundaries of the temporarily occupied territories for the Kherson and Zaporizhzhia regions were drawn quite approximately based on an integrated analysis of data on the boundaries of the occupation zones as of the end of May 2022 according to publicly available web map data [13, 14].

RESEARCH FRAMEWORK

To analyze the impact of the occupation, mainly geomatics methods, systems analysis methods and machine learning methods were used. In particular, the overlay method and map algebra method were used in desktop GIS [15, 16] even before the beginning of 2022 to calculate bio productivity and moisture indices.

The papers consider aspects of integration of temporal statistical characteristics with spectral and textural characteristics extracted from high-quality Sentinel-2 images using Random Forest classification [17]. The performance and contribution of different combinations is evaluated based on classification accuracy. The results show that the statistical analysis of time series is an effective way of presenting information about the degree of soil moisture. The method uses clear pixels from dense, low-quality images to derive NDVI statistics, thus reducing the influence of random factors such as weather conditions.

Approaches to developing a linear mixed effects (LME) model for poorly calculated areas using time series of Sentinel 1A and 1B images and ground measurements of soil moisture are considered [18]. The model assumes a linear relationship that varies in both time and space between soil moisture and backscatter coefficient. The LSE model can be effectively applied to estimate soil moisture from multi-temporal Sentinel-1 images, which is useful for flood and drought monitoring and improving runoff forecasting.

Techniques for mapping soil moisture and irrigation at the scale of agricultural fields based on the synergistic interpretation of multitemporal optical and synthetic aperture radar (SAR) data (Sentinel-2 and Sentinel-1) were also presented [19]. The resulting irrigation maps were validated using reference fields in the study area. The best results were obtained with classifications based only on soil moisture indicators, with an accuracy of 77%.

An important aspect of the study was the separation of data on the NDVI and NDMI indices exclusively for the territory of the agricultural fields of the two regions, without considering the surrounding roads, settlements, water bodies, forested areas, etc. For this, the model was trained using the Image Analyst module, and the machine learning method integrated with desktop GIS was used: Detect Objects Using Deep Learning [20]. For training the model, the Non-Maximum Suppression parameter was used to detect and remove duplicate objects (Fig. 2).

Fig. 2. Reference set of polygons for training the model for identifying the boundaries of agricultural fields

The model tool processes the input geospatial images that are in the extent of the project map. The following approaches were used to train the model: MaskRCNN Object detection (Fig. 3) and Single Shot Detector (SSD) (Fig. 4) [21].

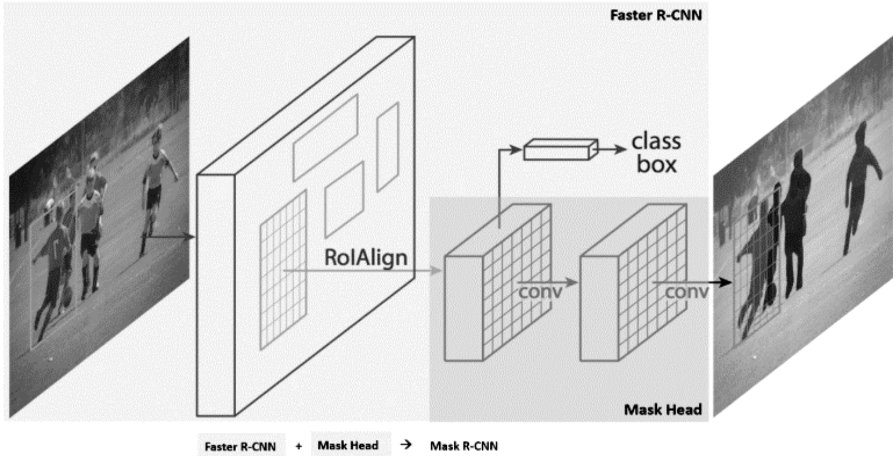


Fig. 3. The Mask R-CNN framework for instance segmentation [22]

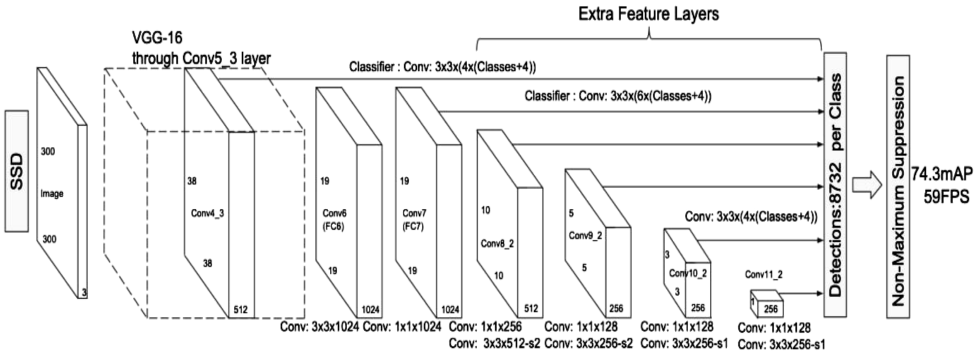


Fig. 4. SSD architecture [23]

The Mask R-CNN is obtainded rablacing the RoI pool by RoIAlign in Faster R-CNN. It helps to preserve spatial information which gets misaligned in case of RoI pool. RoIAlign uses binary interpolation to create a feature map that is of fixed size for e.g. 7 x 7. The output from RoIAlign layer is then fed into Mask head, which consists of two convolution layers. It generates mask for each RoI, thus segmenting an image in pixel-to-pixel manner.

During training our models we need to outline which default boxes correspond to a ground truth detection and train the network accordingly. To achieve this, we need to determine properly objective loss function for SSD model. The SSD training objective is gotten from [24]. Let $x_{ij}^{p} = \{1,0\}$ be an indicator for matching the *i*-th default box to the *j*-th ground truth box of category *p*. In the matching strategy were $\Sigma_i x_{Ji}^{p} \geq 1$. The overall objective loss function is a weighted sum of the localization loss (loc) and the confidence loss (conf):

$$L(x,c,l,g) = \frac{1}{N}(L_{conf}(x,c) + \alpha L_{loc}(x,l,g)),$$

where N is the number of matched default boxes. If $N = 0$, the loss is set to 0. The localization loss is a Smooth L1 loss between the predicted box (l) and the ground truth box (g) parameters. It is regressed to offsets for the center (cx, cy) of the default bounding box (d) and for its width (w) and height *(h)*

$$L_{loc}(x,l,g) = \sum_{i \in Pos}^{N} \sum_{m \in \{cx,cy,w,h\}} x_{ij}^{k} smooth_{L1}(l_i^m - \hat{g}_j^m),$$

$$\hat{g}_j^{cx} = \frac{g_j^{cx} - d_i^{cx}}{d_i^w}, \quad \hat{g}_j^{cy} = \frac{(g_j^{cy} - d_i^{cy})}{d_i^h},$$

$$\hat{g}_j^{w} = \log\left(\frac{g_j^w}{d_i^w}\right), \quad \hat{g}_j^{h} = \log\left(\frac{g_j^h}{d_i^h}\right).$$

The confidence loss is the softmax loss over multiple classes confidences (c):

$$L_{conf}(x,c) = -\sum_{i \in Pos}^{N} x_{ij}^{p} \log(\hat{c}_i^p) - \sum_{i \in Neg} \log(\hat{c}_i^0),$$

where $\hat{c}_i^p = \dfrac{\exp(c_i^p)}{\sum_p \exp(c_i^p)}$ and the weight term α is set to 1 by cross validation.

MaskRCNN and SSD are used for segmentation and precise delineation of object boundaries on a space image.

All calculations of index values were carried out for territories that were within the boundaries of the identified plots. Based on the fact that in the resulting geospatial layers (GSP) there were several million individual values regarding the characteristics of moisture and bio productivity of agricultural fields, the processing results were processed in the R software environment.

Using the capabilities of the Copernicus Open Access Hub [25], images were uploaded to the territory of Kherson and Zaporizhzhia regions for the period May-June 2019–2022. Each image had to be covered by clouds no more than 10%. Due to the presence of many wet atmospheric fronts in the specified period of the year, such a wide permissible time period was chosen for uploading images, where priority was given to space images that were taken in the first half of June (70% of the received images). Due to the unsatisfactory state of cloud coverage of the images, the period of the end of May (12% of the images) and the second half of June (18% of the images) was chosen for the rest of the scenes. For each year, a minimum of 8 separate photo scenes were uploaded, which covered at least 97% of the territory of the selected regions (Fig. 5).

For each year, a new mosaic of both an integral image in the visible range (RGB) and a new mosaic of individual spectral channels (B04, B08, B11) was created from a series of separate images to calculate the moisture and bio productivity indices. Three-spectral rasters in the visible range and single-spectral rasters in the index range were obtained at the output. A raster in the visible range allows you to visually examine the area for artifacts of space images, and, if necessary, replace individual scenes with those that meet the requirements for the visibility of black and white fields. From the new mosaics of individual spectral channels, integral rasters of indices were calculated for each year (Fig. 6).

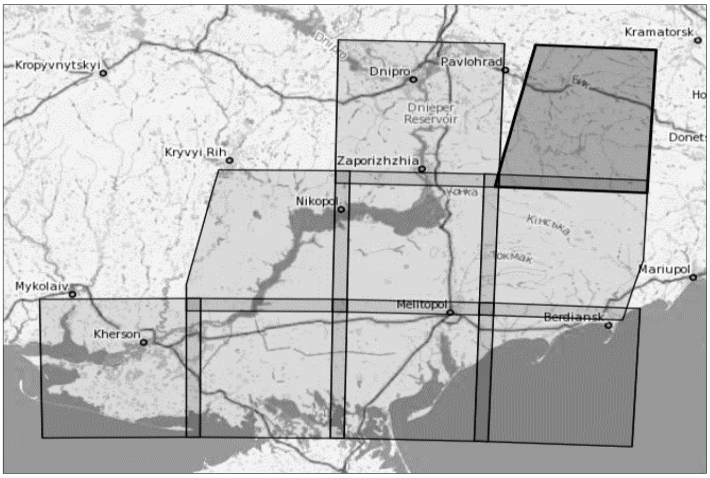


Fig. 5. Coverage of the research area with space images

Fig. 6. A fragment of the territory moisture index raster for 2022

The new image mosaics must be separated from the two areas to avoid analyzing areas that are outside the study ones. To do this, a process of raster extraction along the contours of the Kherson and Zaporizhzhia regions was carried out for all new raster mosaics obtained. The resulting GPS included both those necessary for the analysis of the territory of agricultural fields, as well as external water bodies, urbanized areas, infrastructure facilities, etc. For their illumination and selection of exclusively rural areas, training of a machine learning model integrated into the capabilities of the geographic information system (GIS) was carried out.

To carry out the model training process, it was necessary to manually highlight the boundaries of several thousand agricultural fields on space images for the selected period. The fields were vectorized evenly over the territory of the two regions with important identification of the borders of both irrigated and non-irrigated areas (Fig. 7). Often, irrigated areas have a rather specific contour of a regular circle, which, with insufficient training of the model on these fields, can lead to incorrect identification of boundaries.

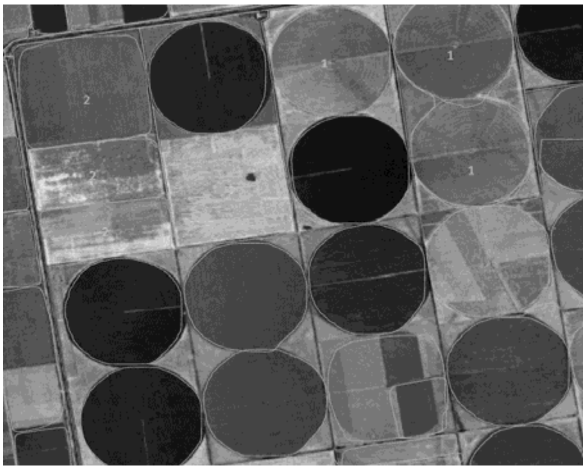


Fig. 7. Characteristic boundaries of irrigated (1) and non-irrigated (2) fields

The training process took place in a GIS environment where image tiles were first created as input layers to train the model. Image tile size was 448 pixels with metadata format: PASCAL Visual Object Classes and RCNN Masks. The image batch size type was 8, the model was run for 100 iterations (epochs). The additional pixel border around each field is 2 pixels. The maximum overlap of the resulting boundaries is 0.1, the minimum reliability of the selected boundaries is 60% (0.6). In total, the model consisted of 12 iterations of corrections and additional training.

As a result, the GIS was obtained with about 370,000 identified agricultural fields for the territory of two regions: 210.000 for the Kherson region and 160.000 for the Zaporizhia region (Fig. 8). The average reliability of the selected limits was 75%.

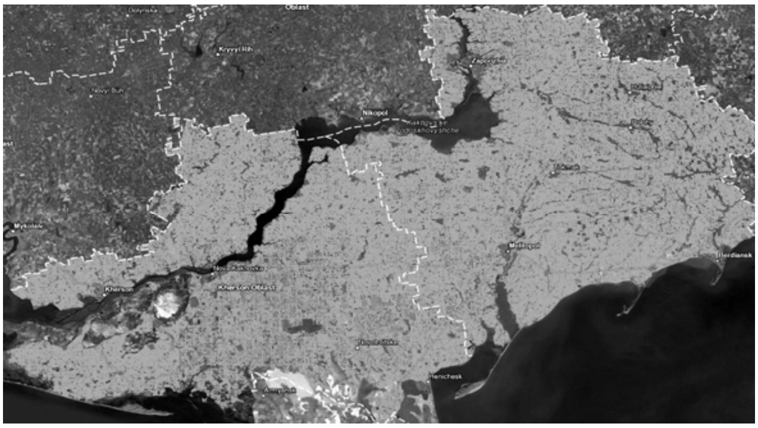


Fig. 8. Identified borders of agricultural fields for Kherson and Zaporizhzhia regions

Further improvement in model accuracy can be performed to achieve other applied goals in agriculture. For assessing the degree of transformation of the moisture regime and bio productivity of the fields, the obtained reliability is considered completely satisfying.

The extraction of new raster mosaics of the moisture index and bio productivity was carried out based on the obtained field mask. The final rasters began to calculate data exclusively for agricultural plots (Fig. 9).

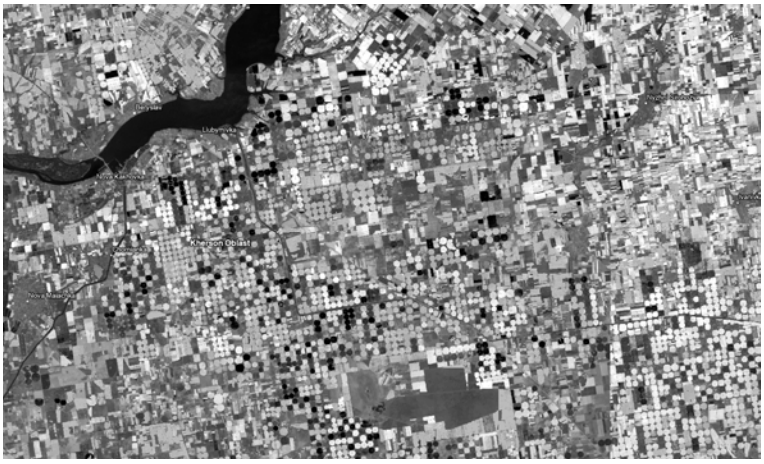


Fig. 9. A fragment of the moisture index raster for agricultural fields in 2022

To assess the state of agricultural fields within individual regions, districts and communities, in the context of temporarily occupied and government-controlled territories, it is necessary to convert raster images into vector format and supplement the GIS with attributive data of the layers of the administrative-territorial system (ATU). After converting the data into a vector format, the area of each cell of the new GPS was calculated to obtain the ratio of the areas of areas with different humidity for each unit of ATU. The resulting layers consisted of more than 10 million records, the calculation of which was extremely difficult exclusively with GIS tools, so the corresponding statistical processing was carried out in the R software environment.

THE MOISTURE LEVEL ANALYSIS FOR THE IDENTIFIED FIELDS

Based on the rasters of the thematic indexes of agricultural fields, it is possible to make a preliminary integrated analysis for two regions, without dividing the regions into districts, communities, and the zone of occupation. Using the methods of zonal statistics, data were obtained on the average values of the moisture index rasters for 2019–2022 (Fig. 10). It can be seen from the graphs that over the past 4 years there has been a rather strong spread of index values: from 0.02 in 2020 to 0.07 in 2019. Moreover, the structure of the distribution of values is not uniform: normal or lognormal distribution in 2019 and 2020, and a distribution with two peaks in 2021 and 2022, indicating dry periods with a strong influence of irrigation systems in particular.

A normal or lognormal distribution indicates the classic case in which the average values of the wetness index cover a larger area. The values for 2019 correspond to this distribution, with a certain local peak on the graph for values that characterize low, poorly moistened vegetation. Most of the territory, according to the distribution, is covered with medium-low vegetation with low water stress. The log-normal distribution for 2020 is characterized by a large peak in the plot for coverage for low and dry vegetation, resulting in an overall lowest 4-year mean wetness index value. This situation strongly correlates with climate indicators, according to which 2020 was the driest year in terms of precipitation, which caused a sharp drop in water levels in natural and anthropogenic reservoirs in the region. For 2021, two peaks on the graph are characteristic: for low and poorly moistened vegetation, and for medium-high, medium with low water stress. This distribution is caused by the contrasting weather conditions in May–June 2021, when the dry period ended with intense precipitation combined with a strong contrast in the wetness index for irrigated and non-irrigated areas. Where the high value of the index is characteristic mainly of irrigated fields, which occupy significant areas in the Kherson region. This statement is supported by further research. The year 2022 is also characterized by two peaks on the graph, among which the larger peak is responsible for poorly watered areas, and the smaller one is for vegetation with low water stress.

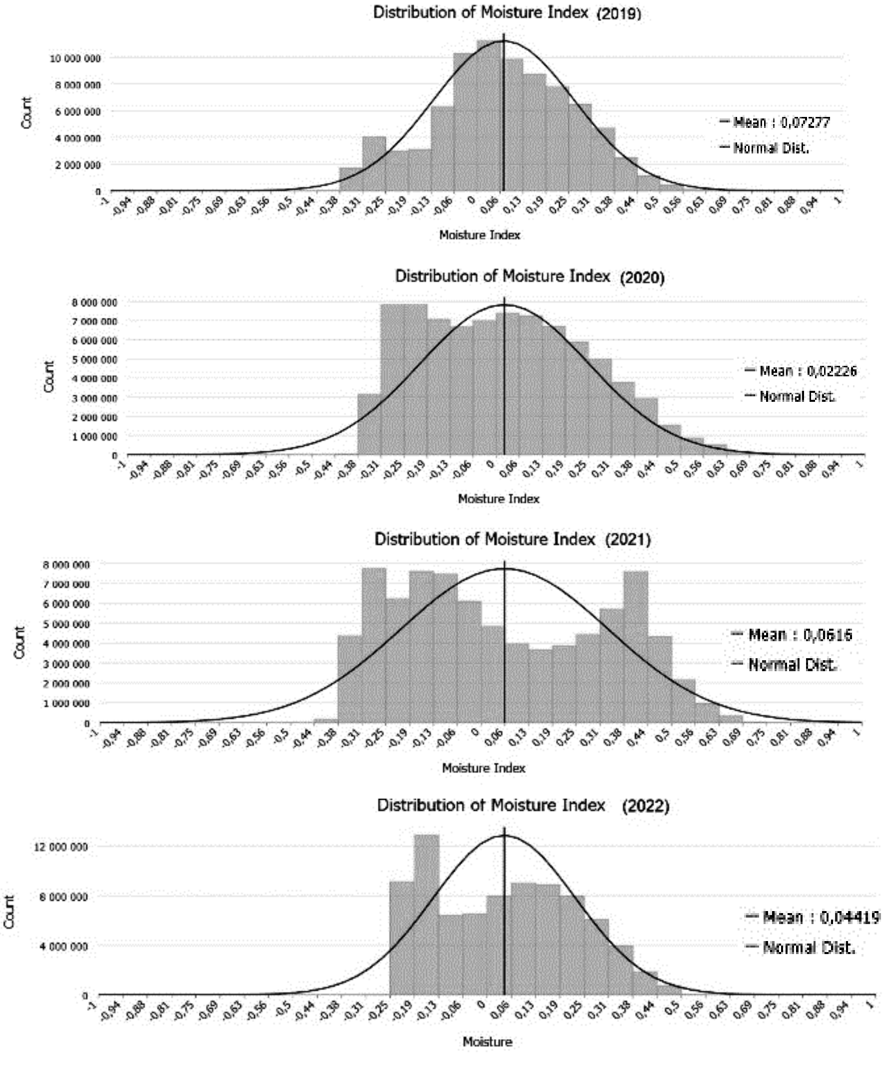


Fig. 10. Distribution of the humidity index for 2019–2022 in the Kherson and Zaporizhia regions

The territorial analysis of the moisture content of agricultural fields for 4 years showed a decrease in plots with medium-high vegetation cover and low water stress in two regions in 2022 (Fig. 11).

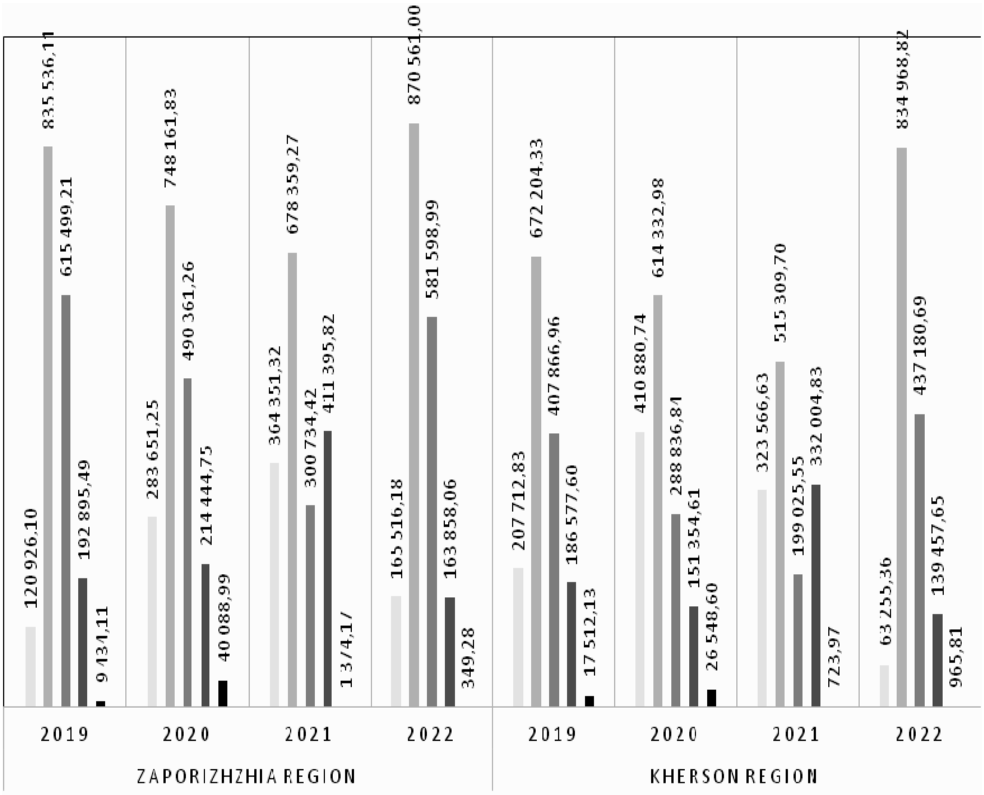
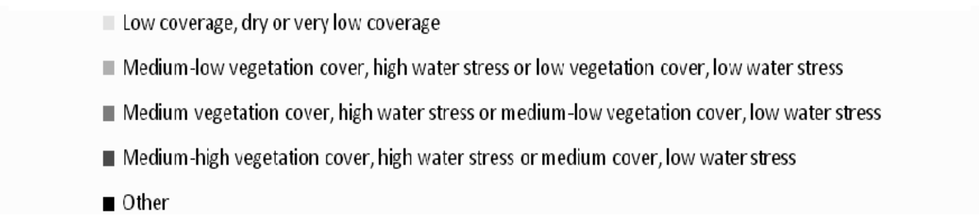


Fig. 11. Dynamics of the humidity index of the territory



Even compared to 2020, when a dry period was observed in both regions, the area of fields with low water stress in 2022 decreased by 8% in Kherson region and by 24% in Zaporizhzhya region. The Kherson region has a larger number of irrigated areas, which, most likely, continued to be actively irrigated in 2022, which quite strongly smoothed out the drop in the index value. Compared to the previous year 2021, for 2022 the drop was 60% for both Kherson and Zaporizhzhia regions. Such a rapid decrease in well-watered agricultural fields can be explained by the transformation in the conduct of irrigation and other processes in the agriculture of the region, which, in turn, is most likely directly related to the temporary occupation of the region. This statement requires further research in the context of expanding the experimental period of observations of the dynamics of the territory's moisture index. Most likely, there is a certain shift in the phases of irrigation, which leads to a shift in the vegetation phases of agricultural plants. From the graph of the dynamics of the index, it can be seen that in 2022 there is a significant increase in the area of fields with medium-low vegetation cover and low water stress compared to all other years: an increase of 119% in Kherson region and 93% in Zaporizhia region compared to 2021 However, compared to 2019, there are almost no changes in areas, which most likely indicates a significant influence of climatic factors on the value of the indicator.

The influence of climatic factors, namely a rather cold and wet spring, also affected the distribution of areas with dry and very low vegetation cover (Fig. 12).

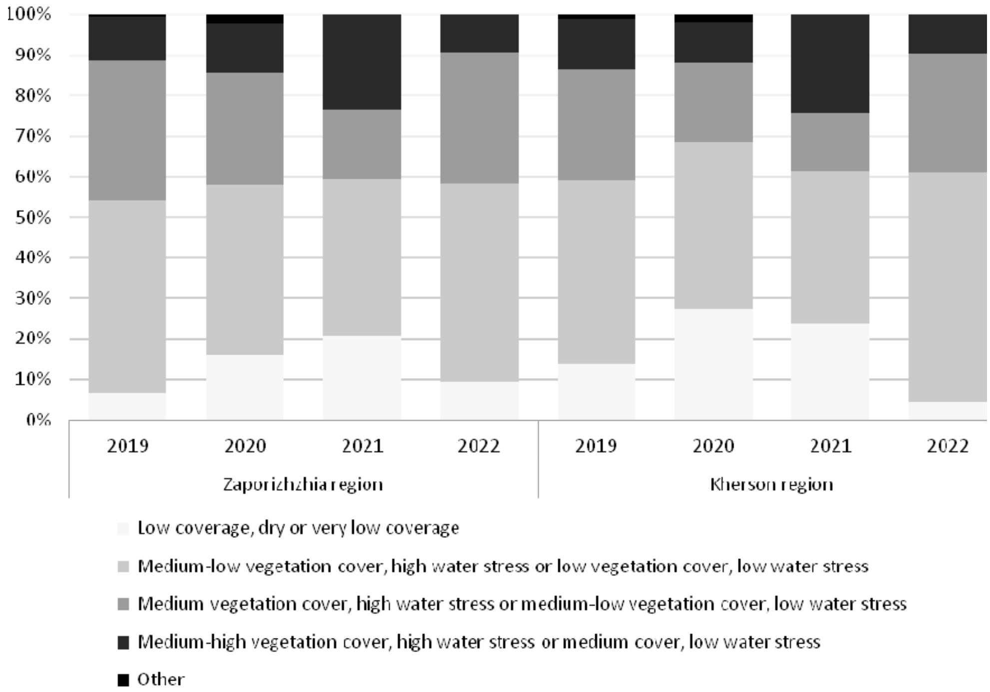


Fig. 12. Percentage distribution of the territory's humidity index values

In 2022, there is a drop in this indicator compared to other years. This is especially characteristic of the Kherson region, where favorable synoptic conditions combined with artificial irrigation processes significantly reduced the index with low values.

An analysis was conducted exclusively for irrigated fields. For this purpose, those that are not reached by the system of irrigation canals were illuminated from the entire array of plots. The situation with the irrigated area is quite dynamic, so the average indicator of irrigated areas over 4 years was chosen. The Kherson region has a much higher density of canals and irrigated areas in general (Fig. 13). Therefore, fields with low water stress occupy much more area in the Kherson region, where there are almost no irrigated fields with dry vegetation (less than 4%).

Territorial analysis of the influence of occupation, in contrast to the temporal distribution, did not show any differences in the condition of agricultural fields in temporarily occupied and unoccupied areas of the region. Intense hostilities affect the entire territory of the regions, where the demarcation zone dynamically changes many times a month. Moreover, the most cultivated and irrigated parts of both the Kherson and Zaporizhzhia regions have been under temporary occupation since the first days of the war, the unoccupied territory consists of fields that are not reached by canal branches. This condition leads to a slight proportional increase in the area of poorly moistened areas precisely in the unoccupied territories (Fig. 14). However, all other index values remain proportionally almost the same.

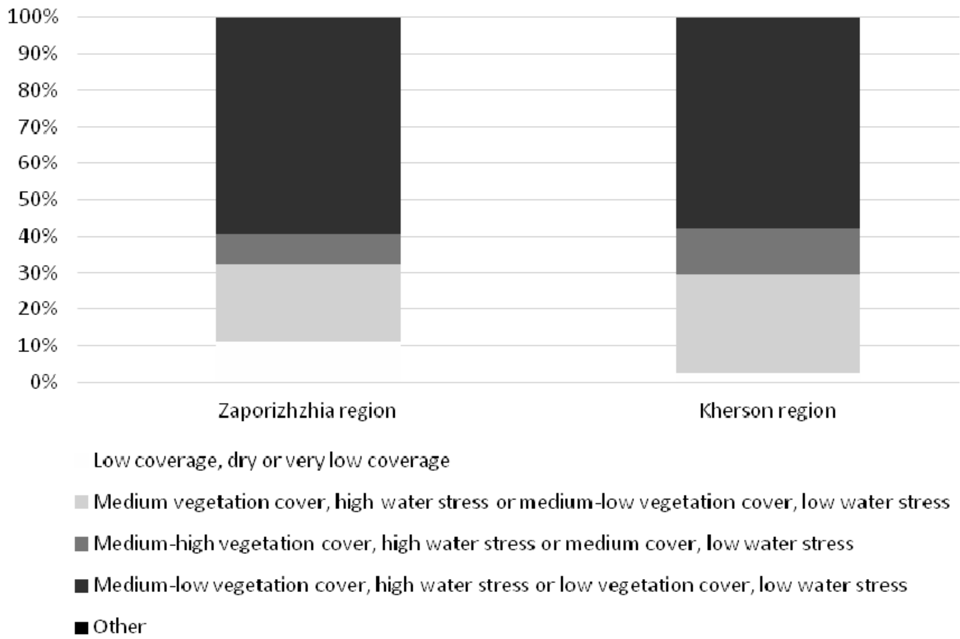


Fig. 13. Correlation of moisture index values for irrigated areas in 2022

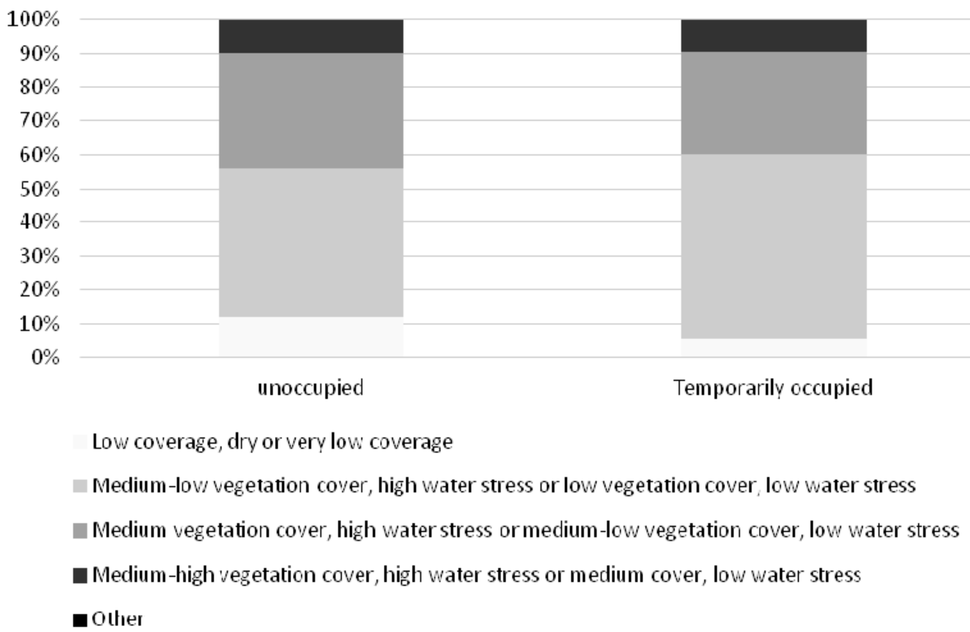


Fig. 14. Differentiation of the humidity index in temporarily occupied and unoccupied territories

CONCLUSIONS

1. The temporary occupation of the part of the Ukraine's southern regions leads to significant transformations in the structure of agriculture. Even though almost all the capacities of the irrigation systems of the Kherson and Zaporizhia regions was under the control of the occupiers, there is a significant decrease in

agricultural fields in a well-watered state (up to 60% compared to previous years). This may indicate the imperfect use of existing irrigation facilities and the reluctance of local farmers to cooperate with the occupation authorities.

2. However, at the same time, the catastrophic impact of temporary occupation on the state of agricultural land is not observed. Most of them are in a satisfactory condition, which makes it possible to predict a slight decrease in the amount of potentially harvested agricultural products. Active military actions do not allow agricultural works to be carried out fully in the unoccupied part of the regions, which affects the state of agricultural crops. However, even in such a difficult situation, the state of moistening of the fields of most of the unoccupied territory remains satisfactory. Which also indicates a favorable forecast for the collection of agricultural crops. However, the factor of conducting hostilities, which can significantly worsen the situation with the state of agricultural fields in both occupied and non-occupied territory, remains unpredictable.

3. The prepared machine learning model for identifying the boundaries of agricultural plots significantly improved the accuracy of the estimates made by illuminating all extraneous territories. In individual communities of the region, without considering the results of the model, the indicators of the state of hydration differed by 10–15% compared to the indicators of the indexes calculated exclusively within the boundaries of the plots.

4. The developed machine learning model can be applied to other regions of Ukraine, which will make it possible to assess the impact of military operations and/or temporary occupation for all affected regions. It is urgent to expand the research area in the following research to Mykolaiv region, which was also significantly affected by the temporary occupation of its territory.

5. Similar methods can be applied to those regions that have not undergone occupation, in the context of temporal and territorial analysis of the condition of agricultural fields under conditions of climate change, etc.

FUNDING INFORMATION

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ДОСЛІДЖЕННЯ ПРОБЛЕМ ПРОДОВОЛЬЧОЇ БЕЗПЕКИ, ОХОПЛЕНИХ ВІЙНОЮ РЕГІОНІВ УКРАЇНИ МЕТОДАМИ ГЕОМАТИКИ / М.З. Згуровський, К.В. Єфремов, С.В. Гапон, І.О. Пишнограєв

Анотація. Світ з кожним роком наражається на нові важкі виклики щодо підтримання глобальної безпеки. Важливою складовою глобального контексту світового розвитку є дотримання принципів продовольчої безпеки. Новітні військові конфлікти сильно впливають на стан розвитку регіонів, які забезпечують мільйони людей по всьому світу продовольством. Україна відіграє ключову роль у глобальних процесах забезпечення продукцією сільського господарства населення країн з різних континентів. Присвячено дослідженню станів сільськогосподарських культур у регіональному розрізі у період ведення активних бойових дій засобами геоматики, що дозволяє швидко оцінити ступінь трансформації сталого господарювання, визначити тренд розвитку галузі, обчислити ймовірні масштаби зміни отриманої про-дукції у найближчі роки. У результаті за допомогою інтегрованих у геоінформаційні системи моделей глибинного навчання визначено межі сільськогосподарських полів Херсонської та Запорізької областей, стан зволоженості та біопродуктивності сільськогосподарських культур за три роки, проаналізовано зміни станів сільськогосподарських полів під впливом нових факторів ведення активних бойових дій за першу половину 2022 р., зроблено прогноз продуктивності наступного врожаю у двох південних областях України. Наведене дослідження виконано командою Світового центру даних «Геоінформатика та сталий розвиток» КПІ ім. Ігоря Сікорського і є частиною досліджень з аналізу поведінки складних соціально-економічних систем та процесів сталого розвитку в контексті якості та безпеки життя людей.

Ключові слова: продовольча безпека, просторовий аналіз даних, глибинне навчання, сільськогосподарські поля, математичне моделювання.