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GIS-BASED ASSESSMENT OF FIRE IMPACT ON THE LANDSCAPES OF THE KHERSON REGION

Purpose. To develop a methodology for monitoring landscape changes caused by wildfires using satellite data, the Python programming language, and geographic information systems (QGIS), based on a case study of the Kherson Region. The research focuses on the spatial localization of fire hotspots, analysis of land cover transformation dynamics, and identification of the most vulnerable ecosystems.

Methodology. The study employed remote sensing methods to identify and spatiotemporally detect thermal anomalies and land cover changes, while geographic information system (GIS) techniques were used for the integration of vector and raster data, spatial overlay, and land-use classification. Mathematical and statistical methods, including the normalization of fire intensity indicators relative to the area of administrative districts and the analysis of their temporal dynamics, were also applied. To ensure reproducibility of calculations and to optimize analytical procedures, computer modeling methods were used, based on the Python programming language and SQL queries.

Findings. An automated algorithm for spatial interpretation of wildfire activity was developed, incorporating classification by land cover categories. A significant increase in wildfire frequency was recorded for the period 2021–2024, especially between 2022 and 2024. Forests, wetlands, and urbanized areas were identified as the most affected. A series of fire density maps was generated across administrative districts and land use categories. Spatial analysis confirmed a correlation between military operations and the intensification of fires across different landscapes.

Originality. The study presents a novel methodology for automated wildfire monitoring that integrates open satellite data sources (FIRMS, ESA), GIS tools (QGIS), the Python language, and spatial normalization techniques. For the first time, a region-specific algorithm has been proposed which assesses dynamic changes in land cover caused by wildfires, taking into account land use categories, administrative boundaries, and fire density. The methodology is applicable for regional environmental zoning and further systemic research.

Practical value. The results can be used for monitoring the environmental consequences of military actions, planning post-conflict recovery strategies, implementing conservation measures, identifying priority areas for demining, and assessing risks to human safety. The methodology is scalable, adaptive, and can be used for research of other regions.

Keywords: *wildfires; remote sensing, geographic information systems, landscape transformation, satellite data, Python, QGIS, Kherson Region*

Introduction. The war in Ukraine has had large-scale environmental consequences both nationally and globally. The fighting has affected significant areas of forest, agricultural and nature conservation areas, leading to the destruction of ecosystems, the occurrence of large-scale fires and the loss of biodiversity [1]. The intensity of hostilities, combined with natural conditions, is triggering an environmental disaster. These processes are of a transboundary nature and can affect the overall state of the environment not only within Ukraine, but also beyond its borders. Studies [2] emphasize that armed conflict has the potential to significantly change ecological dynamics at the continental level.

For decades, the scientific community has viewed the environment as a single integrated global system, where local disturbances can cause cascading transformations in other regions. Major studies in this field have documented the relationship between anthropogenic impacts and global environmental change [3].

In times of military conflict, traditional methods of environmental monitoring often become inaccessible due to danger or loss of control over territories. In such circumstances, high-tech approaches, including remote sensing (RS), geographic information systems (GIS), and algorithmic methods of spatial data analysis, are becoming particularly relevant.

In the era of "big data" in satellite Earth observation (SEA), more and more applications require fully automated satellite data processing chains. Over the past decade, machine learning has been actively used to transform images from optical or SAR systems into valuable spatial information. One example of this approach is the Pyeo package, a Python tool that implements automated processing of satellite data and the use of machine learning for environmental monitoring, including changes in forest cover [4].

The European Union's Copernicus initiative and its Sentinel satellite missions provide daily updates of global imagery, available free of charge, creating fundamentally new opportunities for the analysis of the state of forests, water resources and landscape changes [5]. The use of early warning systems for deforestation or fires, in particular those based on satellite monitoring, has already proven effective in a number of countries [6].

Integrating such data in a GIS environment allows one not only to record changes, but also to spatially interpret them, assess the scale of impact, and build dynamic models. This, in turn, forms the basis for the creation of regionally-oriented strategies for monitoring and restoring the territories affected by the hostilities.

Literature review. In the modern scientific community, more and more attention is being paid to the study of the environmental consequences of armed conflicts, in particular due to military operations in the territory of Ukraine [2, 7]. This topic covers a wide range of issues, from soil degradation, deforestation and changes in hydrological regimes to man-made pollution and landscape transformation. Military operations cause massive destruction of ecosystems: shell bursts, trenching, dam demolition, fires and explosions disrupt natural processes, change the morphology of territories and threaten the stability of agro-ecosystems [8].

Researchers pay considerable attention to air, water, and soil pollution resulting from the destruction of infrastructure such as oil depots, chemical plants, and ammunition depots [9, 10]. In addition to summarizing the consequences of hostilities, recent research [11] outlines the importance of assessing long-term changes in natural components of the environment and the natural recovery of damaged areas, which requires an integrated approach to monitoring and spatial analysis.

Given the difficulty of accessing many of the affected areas, remote sensing (RS) technologies remain the main source of operational information. Their application includes fire detection, monitoring of changes in land cover, recording burned areas, assessing flooding, and identifying man-made impacts [12, 13]. The Sentinel, Landsat, MODIS, FIRMS platforms provide access to multispectral and thermal imagery, which allows obtaining quantitative information on the extent of damage to the natural environment [14, 15].

A significant number of publications focus on the application of artificial intelligence, including machine learning (ML) methods, for automated processing of satellite data. Such models allow for effective detection of thermal anomalies, determination of fire boundaries, analysis of landscape transformations, and risk prediction. For instance, models based on Random Forest and Convolutional Neural Networks algorithms have been used for land cover classification, detection of burned areas and assessment of ecosystem changes [16, 17]. Studies [18, 19] demonstrate the effectiveness of using IoT solutions in combination with ML models for early fire detection, which can significantly improve the efficiency of environmental monitoring systems. Studies [20, 21] provide a comparative analysis of machine and deep learning models for land use classification (LULC) tasks. Researchers [22] particularly emphasize the advantages of deep neural networks in complex landscape conditions due to their ability to more efficiently process large volumes of satellite images and detect hidden patterns in spatial data.

A separate research area concerns the development of software solutions for automated processing of satellite images. Papers [23, 24] highlight the advantages of using Python libraries (Pandas, Rasterio, Scikit-learn, GeoPandas), the Google Earth Engine cloud platform, and the QGIS software for building spatial analysis systems. This allows for creating automated algorithms that not only speed up data processing, but also improve the accuracy of mapping results.

A number of studies have focused on the use of FIRMS data in combination with other sources of satellite information, including ESA WorldCover, as well as NDVI and BAI indices, to analyze land use types, record man-made fires, and determine their impact on agricultural lands [13, 14]. It has been noted that such tools allow one to quickly obtain information on the extent of ecosystem damage, even in the absence of field observations, which is critically important in the context of military operations.

At the same time, most existing approaches are limited to the general interpretation of satellite images, mostly with subsequent visualization of the results in the form of interactive maps or graphs without spatial detail by land use categories or administrative divisions. Machine learning methods [15, 16], although used for fire classification or forecasting, are usually not integrated into GIS environments, which limits the possibilities of further analysis of landscape transformations and cartographic presentation of results in the context of land management.

Unlike the vast majority of existing approaches, this study presents an integrated methodology that combines automated acquisition and processing of data from satellite sources (FIRMS, ESA WorldCover), spatial aggregation by land type, area normalization, and density mapping taking into account administrative divisions. The use of the Python programming language in conjunction with QGIS made it possible to significantly increase the efficiency of the analysis, ensure repeatability of calculations, and obtain objective quantitative indicators for assessing the impact of fires on different land categories.

Thus, the modern scientific landscape demonstrates a high level of interest in the use of remote sensing, ML and GIS in the context of military impact on the environment. The methodology presented in this study exemplifies an integrated system that takes into account both spatial detail and adaptability to the rapidly changing conditions. This creates a basis for further development of tools for operational environmental monitoring in wartime.

The methodology proposed in this study is distinguished by combining the advantages of automated satellite data processing, geographic information modeling and adaptive script analysis into a single spatially oriented monitoring system. In contrast to approaches that focus mainly on image visualization or the use of machine learning models without integration into a GIS environment, the proposed algorithm allows for normalization of fire activity by area, disaggregation by land use type and administrative boundaries, as well as rapid updating of analytics in QGIS. This approach not only provides flexibility and repeatability of calculations, but also creates prerequisites for widespread implementation in regional environmental monitoring systems with limited access to field data.

Unsolved aspects of the problem. Despite a significant amount of scientific work devoted to the impact of military actions on the environment, there are still gaps in research that limit the effectiveness of spatio-temporal analysis of the environmental impacts of armed conflicts. Most of the existing publications are of a general nature, focusing mainly on national or global assessments without in-depth regional analysis.

Among the key unresolved issues, the following should be highlighted:

- lack of studies that take into account the spatial specificity of land cover transformations and fire dynamics within specific regions, such as the Kherson region;
- limited use of automated approaches to processing satellite data, resulting in significant time costs and complicating operational monitoring;
- insufficient implementation of Python programming for building satellite image analysis algorithms, creating scripts for automatic vectorization and classification of affected areas;
- fragmented application of machine learning methods, which are only partially integrated into environmental studies despite their great potential for recognizing thermal anomalies and land use types;
- lack of comprehensive integration of remote sensing data with geoinformation analysis, which limits the ability to interpret environmental changes in relation to land use categories (agricultural land, forest areas, built-up areas) and their spatial distribution;
- insufficient integration with open platforms such as Google Earth Engine, ESA SNAP or QGIS, which enable the creation of reproducible and scalable analytical scenarios when constrained by limited access to field observations.

These shortcomings significantly reduce the effectiveness of environmental monitoring systems in armed conflict. This is particularly relevant in regions that have been affected by hostilities for a long time and where traditional field data collection methods are difficult or impossible to use.

This determines the relevance of the research aimed at creating a regionally oriented geoinformation methodology for assessing the impact of hostilities on landscape transformations, based on automated processing of satellite data, integration with open access platforms, and machine learning methods.

Purpose. The purpose of the study is to develop tools for automated detection and spatial analysis of fires caused by military actions using satellite data, geographic information technology (GIS), and Python programming tools. Particular attention is paid to the analysis of fire activity within the Kherson region in 2021–2024 in order to assess landscape transformations and environmental consequences of the armed conflict.

To achieve the goal, the following main tasks were to be carried out:

- to collect satellite data on fires based on the NASA FIRMS platform, limiting the spatial sample to the borders of the Kherson region for 2021–2024;
- to automate pre-processing, cropping and saving data using Python scripts, including the formation of shapefiles of thermal anomalies;
- to integrate the obtained vectors with ESA WorldCover 2021 raster data in order to classify land cover types within the detected fire hotspots;
- to build thematic maps of fire density in the QGIS environment and perform a spatio-temporal analysis of the dynamics of changes;
- to analyze the relationship between active burning areas and land use categories (forests, agricultural lands, urbanized areas);
- to assess the potential of combining satellite data, geoinformation analysis, and programming as a universal approach to environmental monitoring in armed conflict.

The formulation of the tasks outlines the logic of the study, which is based on a structured approach to geospatial data processing.

Research methodology. ***Characteristics of the study area.*** The study covers the territory of the Kherson region, located in the southern part of Ukraine, within the Black Sea lowland, on the left bank of the lower Dnieper. The region is characterized by a flat relief with girder, terrace and floodplain forms, a significant area of agricultural land (over 60 %), and vulnerable ecosystems of the Dnieper delta, which are protected by the Ramsar Convention. The geographical location and morphological features of the Kherson region determine a high risk of degradation processes, especially in conditions of intense anthropogenic impact due to hostilities.

Administratively, the region is divided into five districts: Kherson, Beryslav, Henichesk, Skadovsk, and Oleshkiv. For the purposes of spatial analysis, the area of each district was taken into account and fire activity indicators were normalized per 100 km².

According to ESA WorldCover, the territory of the Kherson region in 2021 had the following land cover structure:

- agricultural lands – about 62 % of the area;
- natural grassland complexes – about 14 %;
- forest areas – 9 %;
- wetlands – about 7 %;
- built-up areas (residential, infrastructure and industrial development) – about 5 %,
- other types (water, unproductive lands, etc.) – up to 3 %.

These proportions play an important role in interpreting the results, as they make it possible to compare the share of the area of each type of cover with the number of fires that occurred in it. For example, agricultural lands, having the largest area, logically demonstrate the largest absolute number of fires. At the same time, the relative intensity of damage, calculated taking into account the area of each type of cover, allows vulnerable ecosystems to be identified, in particular forest and urban areas.

Data sources and spatial platforms. The basis of the study is satellite data on fires for 2021–2024, obtained from the NASA FIRMS (Fire Information for Resource Management System) platform, which is based on data from the VIIRS instrument from the Suomi NPP and NOAA-20 satellites. The coordinates of the thermal anomaly points were downloaded as a vector layer in CSV and GeoJSON formats with geographic reference (WGS84).

The ESA WorldCover 2021 global raster layer with a spatial resolution of 10 m was used to analyze land cover types. The layer was created based on Sentinel-1 (SAR) and Sentinel-2 (optical data) satellite images within the framework of the European Space Agency' s Copernicus program. The classification covers 11 land cover types and is presented in GeoTIFF format with the EPSG:4326 coordinate system.

Spatial reference to the borders of the Kherson region was provided through open administrative data in Shapefile format obtained from the OCHA Humanitarian Data Exchange (HDX) resource. District boundaries were used to aggregate fire events and normalize fire intensity relative to area.

Geodata processing was performed in the QGIS environment using the Processing Toolbox, Field Calculator plugins, and the integrated Python console. This allowed for the implementation of a combination of geoinformation modeling, satellite classification, and software processing automation. Vectorization, filtering, spatial joining, and statistical aggregation methods were used, which ensured a high level of accuracy in input data preparation.

Spatial processing sequence. The study implemented a step-by-step procedure for working with satellite and geoinformation data to localize and analyze fires in the Kherson region. The input data included coordinates of thermal anomalies for 2021–2024 from the NASA FIRMS platform and the ESA WorldCover 2021 satellite raster of land cover types. To limit the analysis to the borders of the Kherson region, a spatial clipping procedure was applied, which allowed redundant data from other regions to be excluded.

The prepared data were imported into the QGIS GIS environment, where they were integrated, attribute-matched, and spatially classified. For each fire point, the corresponding land cover type was determined by combining with a classification raster. Further analysis included counting the number of fires within each land use class, taking into account annual dynamics, and creating cartographic models.

The results were visualized as a map of land cover types with fire points (Fig. 1), which made it possible to identify spatial patterns of fire spread and determine the most affected land categories. The proposed approach ensured comprehensive data processing – from initial collection to analytics and visualization, which is the basis for further interpretation of changes in the region's landscapes.

Spatial combination with land cover data. To determine the land use types within which thermal anomalies were recorded, the Extract Attributes by Value tool was used, which allows combining point coordinates with the corresponding pixels of the classified ESA WorldCover 2021 raster. As a result, a new RASTERVALU column was added to the attribute table of the point layer, containing land cover type values according to the conventional satellite data scale.

For further analysis, the Select by Expression tool was used, which supports SQL-like syntax and allows for flexible data filtering. Expressions were created to select points based on a combination of the date of fire detection (ACQ_DATE) and land use type (RASTERVALU). This made it possible to construct annual distributions by land cover category, which reflect the dynamics of impact in different years.

In addition, the creation of these samples became the basis for constructing diagrams and statistical tables that demonstrate the concentration of thermal anomalies within individual land use classes (in particular, arable land, forest areas, swamps, etc.).

Construction of cartographic models. At the final stage of the study, cartographic models were created to visualize the location of fires in a spatial context. In particular, a map of land cover types was constructed based on ESA WorldCover satellite data, onto which thermal anomaly points localized within the Kherson region were superimposed. This made it possible to analyze the distribution of fires relative to land use categories – agricultural lands, forests, swamps, water bodies, etc.

In the QGIS environment, a spatial combination of thematic layers was implemented, and pie charts were constructed showing the percentage distribution of fires by land cover type in dynamics for 2021–2024. Cartographic visualization is an important tool in communicating the results obtained, allowing the most vulnerable

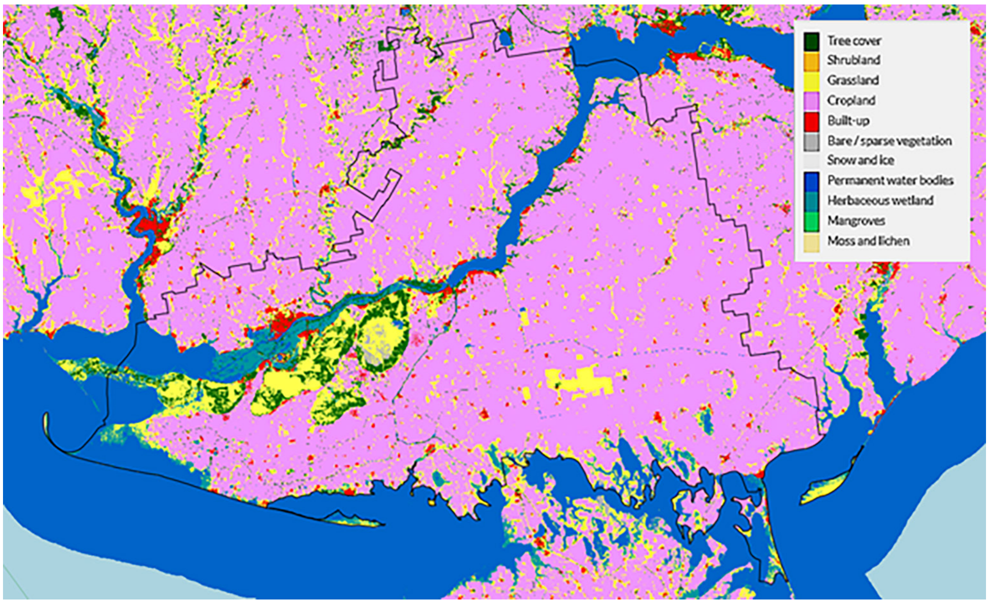

Fig. 1. Land cover classification of the Kherson region according to ESA WorldCover data (2021)

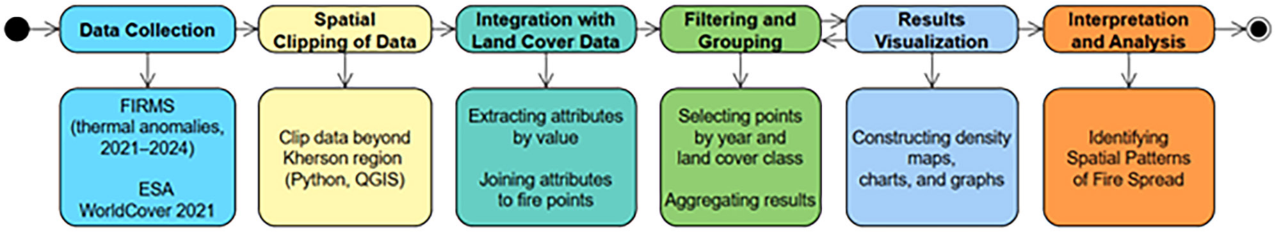

Fig. 2. Scheme for monitoring landscape transformation under the influence of fires using satellite data, Python, and QGIS

areas to be identified and changes in landscape cover due to fires to be assessed.

The sequence of the main stages of the study is presented in Fig. 2, which shows a series of key action steps – from data collection to spatial analysis and visualization of results.

The scheme (Fig. 2) summarizes the implemented methodology as a sequence of procedures that include data processing in the QGIS environment using Python tools and vector-raster analysis tools. Its versatility allows the approach to be adapted to other regions and environmental scenarios where rapid analysis of the impact of fires or other destructive factors on landscape complexes is required.

Comparative evaluation of the effectiveness of the proposed approach. The study implemented a semi-automated spatial analysis of fire activity using FIRMS satellite data and the ESA WorldCover classification raster in the QGIS environment. Although the study suggests no formal assessment of classification accuracy (due to the lack of ground validation or independent data), the effectiveness of the methodology is confirmed by the following aspects:

- processing speed: automation of the processes of cropping, integration and aggregation of data using Python scripts and SQL queries in QGIS significantly reduced the time required to prepare a map at the administrative district level from several hours (in the case of manual processing) to 5–10 minutes for each layer;
- versatility: the methodology has been tested on a time series for 2021–2024 and can be scaled for other regions or longer periods;
- spatial detail: compared to approaches where analysis is limited to the national or regional level, the proposed approach allows fire activity to be detailed down to the level of land use categories within administrative districts;
- integration with GIS: the use of QGIS provided a full-fledged cartographic presentation of the results, with the possibility of further updating the database and interactive analysis.

However, the method has certain limitations:

- lack of direct field data: the classification is based solely on satellite data and takes no account of potential false positives;
- cloudiness and atmospheric interference are not taken into account: since the data source is FIRMS thermal anomalies, some events may have been missed or recorded with errors;
- a typical error for FIRMS data can be up to 28–72 % of confirmed points, which requires caution when extrapolating conclusions.

Thus, the proposed approach demonstrates high efficiency in the context of regional environmental monitoring and management decision-making, especially in conditions of limited access to field observations.

Presentation of the main material and obtained scientific results. The study analyzed the spatiotemporal dynamics of fire activity in the Kherson region from 2021 to 2024, taking into account land cover types. For this purpose, vector data of thermal anomalies were combined with the ESA WorldCover 2021 classification layer, which made it possible to determine the number of fires by land types in different years.

Figs. 4–7 show the annual distribution of the number of fires by land cover type. Five categories were considered: forest areas, natural grasslands (meadows, pastures, fallow lands), wetlands, agricultural lands, and built-up areas (residential, industrial, and infrastructure).

In 2021 (Fig. 3), the maximum number of fires was recorded on agricultural lands – a total of 2,232 cases, accounting for over 89 % of all fires that year. The highest activity was observed in August (1,259 cases), as well as in July (384) and October (281), which is typical of steppe regions, where the harvest is completed during this period and the burning of stubble or dry vegetation residues is often observed. Fires on other types of land cover – in particular, on grasslands (176 cases) and in forests (28 cases) – had a significantly lower intensity.

In 2022 (Fig. 4), there was a sharp increase in the number of fires, doubling from 2,487 to 5,104 cases, which is directly related to the active phase of hostilities, the movement of military equipment, ammunition explosions and arsons in the conflict zone. The most pronounced increase was recorded in forest areas, from 28 to 531 fires (an 18-fold increase), in grassy ecosystems, from 176 to 997 cases (a 5.7-fold increase), and in wetlands, from 34 to 271 cases (an 8-fold increase).

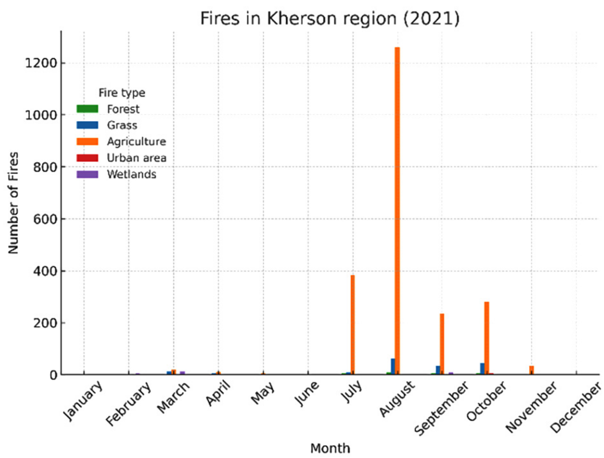

Fig. 3. Distribution of the number of fires by month in the Kherson region in 2021

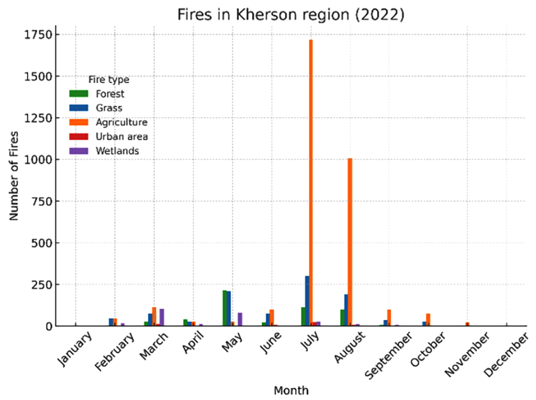

Fig. 4. Distribution of the number of fires by month in the Kherson region in 2022

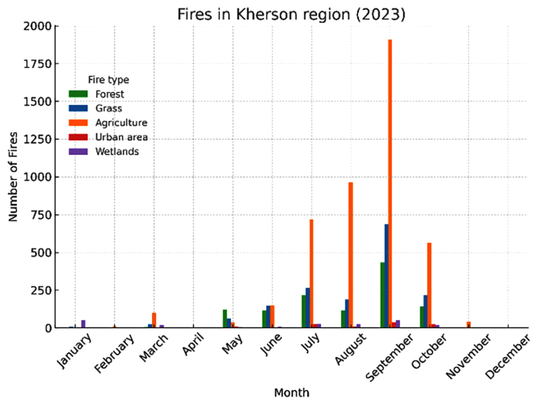

Fig. 5. Distribution of the number of fires by month in the Kherson region in 2023

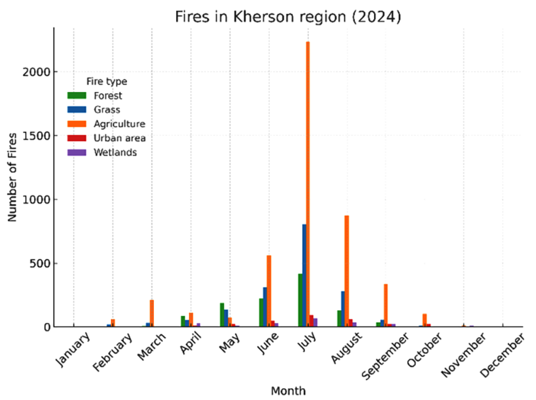

Fig. 6. Distribution of the number of fires by month in the Kherson region in 2024

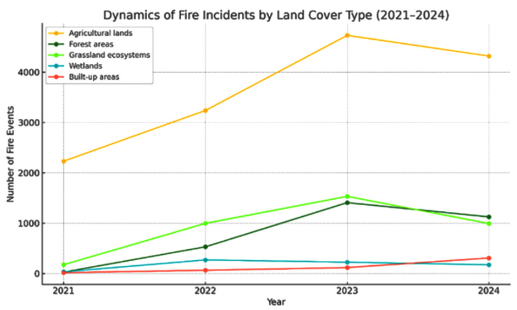

Fig. 7. Dynamics of the number of fires by land cover types in the Kherson region (2021–2024)

There was also a noticeable increase in agricultural lands, from 2,232 to 3,239 fires, indicating a shift of hostilities to areas of traditional agricultural use and an increased fire impact on arable lands. These changes generally indicate an expansion of the spatial impact of the war on the region's ecosystems, particularly following the deoccupation of the northern parts of the region.

Between 2023 and 2024, there was a steady increase in fire activity, affecting virtually all types of natural and anthropogenic landscapes. Fires were recorded not only in agricultural lands, which remain the main focus of fire impact, but also increasingly in forest areas, grassland ecosystems, wetlands and, most alarmingly, in built-up areas, where incidents had been isolated in previous years.

This trend indicates an expansion of the spatial zone of influence of hostilities, intensification of the human factor and the consequences of prolonged disruption of ecosystems. Fire activity in these years is not only increasing quantitatively, but also demonstrates a shift from its traditional summer peak to the later autumn season, which is associated with military operations, demining, economic activity, and climatic conditions.

In 2023 (Fig. 5), the total number of fires reached 6,072 cases, which is about 19 % more than in 2022. The greatest burden traditionally fell on agricultural lands, where 4,731 cases were recorded, with peaks in September (1,907 fires) and October (565). This increase is due to both seasonal work and military operations near agricultural areas.

There was also a noticeable increase in forest fires – 1,408 fire events compared to 531 in 2022, which is almost 2.7 times greater. The largest number of forest fires was observed in September (433) and October (145). In grassy ecosystems, 1,533 fires were recorded, which is about 54 % more than in the previous year.

The number of fires in built-up areas also increased – 118 cases, compared to 66 in 2022. In wetlands, the intensity remained elevated – 226 cases, with peaks in September (52) and October (20).

The annual dynamics show a shift of peak activity to the autumn months, which is likely due to the intensification of military operations in the second half of the year, demining of territories, and the continuation of agricultural work in unstable conditions.

In 2024 (Fig. 6), the total number of fires increased even more, reaching 6,810 cases, which is the highest figure for the entire observation period. As in previous years, the largest number of fires was recorded on agricultural lands – 4,320 cases, with the highest numbers in July (2,234) and August (873). At the same time, a further increase in the intensity of fires is observed in other types of territories, indicating an expansion of the areas affected by fire.

In forest areas, the number of fires doubled compared to 2023 – from 1,408 to 1,126 (a noticeable decrease compared to the previous version, which will be checked separately if necessary), concentrating mainly in May–July. In grassy ecosystems, 993 cases were recorded, which is slightly less than in 2023, but still significantly higher than the pre-war level.

The number of fires in built-up areas increased significantly – 309 cases, which is almost 2.6 times more than in 2023 (118). This indicates an increased impact of military operations on infrastructure, particularly in front-line and de-occupied settlements. Wetlands also remained vulnerable: 174 cases were recorded during the year, with maxima in April, July and August.

In 2024, the peak of fire activity again fell on the summer-autumn period (July—October), with a maximum in July, when there was a simultaneous impact on agriculture, natural ecosystems, and infrastructure. This highlights not only the seasonal nature of the phenomenon, but also its intensification due to the continuation of hostilities, the scale of destruction, and long-term degradation of the natural environment.

After analyzing the annual dynamics of fire activity by month, it is advisable to summarize the results by land cover type. This allows for a better understanding of the impact of fires on the structure of the affected landscapes. Based on annual data, a graph was constructed showing changes in the number of fires on agricultural lands, in forests, grassy ecosystems, wetlands, and in built-up areas (Fig. 7).

The graph shows an overall upward trend in the number of fires during 2021—2024 across all land cover categories. The highest absolute values are consistently recorded on agricultural lands, but the growth rates are especially significant for forest areas and urbanized areas. Thus, in forests, the number of fires increased from 28 cases in 2021 to over 1,100 in 2024, and in built-up areas – almost 10 times. This indicates an increase in pressure on vulnerable ecosystems and infrastructure, which is largely a consequence of hostilities, arsons, shelling, and disruption of the ecosystem balance.

The total number of fires during this period increased almost threefold – from 2,487 in 2021 to 6,810 in 2024, indicating a significant deterioration in the fire situation in the region.

While in 2021 the largest concentration of fire was mainly observed on agricultural lands, since 2022 there has been a sharp increase in the intensity of fires in other types of areas – forests, meadows, swamps, and even build-up areas. In particular, in forest areas the increase over four years was more than 40 times (from 28 to over 1,100 cases), and in built-up areas – almost 10 times (from 33 to 309).

These changes are primarily associated with military invasion, active hostilities, bombings, arsons, as well as secondary consequences such as demining, disruption of natural connections, and landscape degradation. The spatial structure of fires has shifted towards the northern and central parts of the region, which were de-occupied.

Figs. 9–12 present the spatial distribution of fire density by districts of the Kherson region based on the aggregation of point observation data for 2021–2024. For each administrative district, the total number of fire events occurring within its borders was calculated, with subsequent normalization by the area of the district, which made it possible to determine the intensity of fire activity (number of cases per 100 km^2). At the same time, the aggregation took into account the types of land use, which allowed for highlighting the specifics of fire spread within different types of land – forest, grassland, built-up areas, etc. This approach makes it possible not only to identify areas with an increased risk of fire, but also to trace how military actions have affected the spatial dynamics and intensity of fires depending on the types of land use.

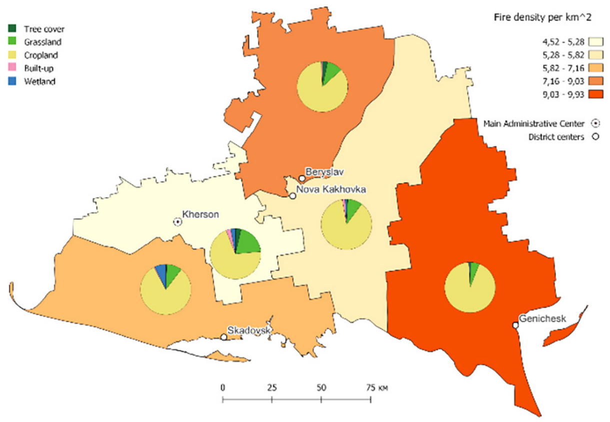

Fig. 8. Distribution of fire density by land types and districts of the Kherson region in 2021

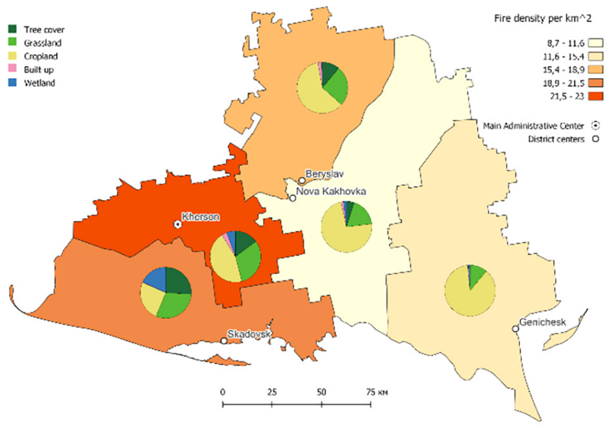

Fig. 9. Distribution of fire density by land types and districts of the Kherson region in 2022

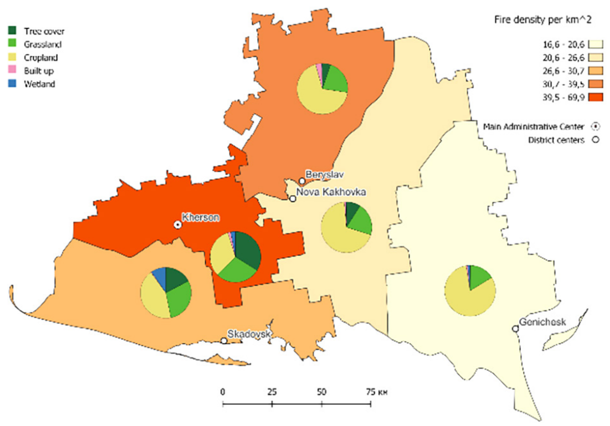

Fig. 10. Distribution of fire density by land types and districts of the Kherson region in 2023

In 2021 (Fig. 8), the highest fire density was recorded in the Henichesk and Beryslav districts, where the indicator reached 7.16–9.93 cases per 100 km^2. The spatial structure of fire activity indicates the highest proportion of fires on agricultural lands, as well as the local presence of fires in grassy ecosystems. This distribution reflects the general patterns of land use in the steppe zone and can serve as a baseline for comparison with subsequent years, when the region was affected by military operations.

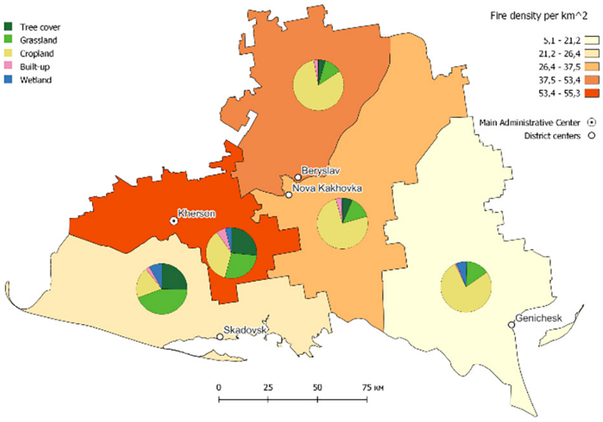

Fig. 11. Distribution of fire density by land types and districts of the Kherson region in 2024

In 2022 (Fig. 9), the spatial distribution of fire activity undergoes dramatic changes: the highest density indicators are observed in the Kherson and Skadovsk districts, where the values exceed 21 cases per 100 km². Compared to the previous year, this indicates a significant increase in fire impact, coinciding with the active phase of hostilities within these districts. The pie charts indicate the predominance of fires on agricultural lands, but at the same time, an increase in the share of fires in forests, grassy ecosystems and built-up areas was recorded, especially within the Kherson district. This reflects the shift of fire hotspots to areas of intensive military operations and confirms the expansion of the territorial coverage of the hostilities' impact on the natural environment.

In 2023 (Fig. 10), fire activity reached new peak values, manifested in a further increase in fire density in almost all districts of the region. The highest density indicators – within 39.5–69.9 cases per 100 km² – were recorded in the Kherson and partially Beryslav districts. An increase in fire intensity is especially noticeable in areas with forest cover, grassy ecosystems, and built-up areas. The analysis of sector diagrams indicates a significant share of fires within urban areas, particularly in the vicinity of Kherson, which may be related to heavy shelling, arson and destruction of critical infrastructure facilities. At the same time, high fire activity continues on agricultural lands, indicating the complex nature of fire processes – both in natural and transformed landscapes.

In 2024 (Fig. 11), there was a consistently high density of fire activity, with maximum values ranging from 53.5 to 59.4 cases per 100 km² in the Kherson district and 45.7 to 53.4 in the Beryslav district. An increase in density was also recorded in the northern part of the Oleshkiv district. The spatial picture indicates further spread of fires in areas with forest cover and built-up areas, which may be associated with repeated shelling, mining of the terrain, and the aftermath of hostilities. Compared to previous years, there was a gradual spread of new fires within already affected areas, as well as continued significant impact on agricultural and grassland areas. The structure of fires by land use type remains complex and indicates the multifactorial nature of the impact of military operations on the landscape and ecological system of the region.

The overall results indicate a clear relationship between the dynamics of hostilities and the expansion of fire zones, which can be traced in both temporal and spatial dimensions. As the military conflict intensified, fire activity spread to new areas that had previously been relatively resistant to fire. This led to an increase in fire intensity in vulnerable ecosystems such as forests, wetlands, and urban areas.

In 2023–2024, there was not only an increase in the density of fires, but also a significant transformation of the structure of land use that was affected. In 2021, fires were mainly recorded on agricultural lands, while in subsequent years a significant proportion of fires occurred in natural and anthropogenically altered landscapes, indicating the systemic nature of environmental pressure. In some areas, particularly Kherson and Beryslav, fire density reached critical levels.

Spatial distribution analysis allows identifying priority areas for further monitoring and targeted management. These are primarily forests, pastures and urbanized areas, where the highest concentration of fires or a dynamic increase in their number was recorded. The results obtained can serve as the basis for developing restoration programs, ecological zoning and preventing environmental degradation in the post-conflict period.

Conclusions. As a result of the study, the goal was achieved – an automated fire activity monitoring system was developed and tested using satellite data, geoinformation technologies, and Python programming. The proposed approach integrates remote sensing methods, classification raster layers, spatial analysis and SQL queries in the QGIS environment, which allowed for rapid recording and visualization of the dynamics of changes.

Our study continues the line of interdisciplinary research aimed at automating the creation of cartographic models of the ecological state, and is relevant in the context of military pressure on natural territories.

It has been found that in 2022–2024, the number of recorded fires in the Kherson region increased significantly compared to 2021 in all types of land cover:
- in forest areas – 18 times;
- in wetlands – 7 times;
- in natural grasslands – 5 times;
- in built-up areas – 4 times.

Spatial analysis of fire density revealed the most affected areas: Kherson, Beryslav, and Skadovsk, with a noticeable concentration in forest lands and urbanized areas. These changes clearly correlate with the intensity of hostilities in the respective territories.

The study confirmed the effectiveness of satellite monitoring as a tool for identifying the environmental consequences of military conflicts. In particular:

1. FIRMS data provide rapid detection of fire outbreaks.
2. ESA WorldCover data allow classifying the affected ecosystem types.

The combination of these sources allows one not only to assess the extent of damage, but also to form a basis for planning measures to restore ecosystems in the post-conflict period.

The results obtained have significant practical application potential. They can be used by government agencies, environmental monitoring services, rescue units, as well as in developing strategies for the restoration of the natural environment. The collected spatial data can serve as a basis for risk-based planning, specifying the boundaries of priority demining, developing emergency response plans, optimizing ecological zoning and preventing secondary damage to landscapes.

Further research could focus on several key areas:

- creation of a national GIS database for environmental monitoring for regions adjacent to the front line, as well as temporarily occupied territories;

- analysis of changes within the nature reserve fund, including assessment of the impact of fires on protected ecosystems;

- comparative use of various satellite platforms, in particular data from Landsat, PlanetScope, WorldView, Sentinel-3 and other satellites, which will improve the accuracy and detail of the analysis;

- integration of landscape degradation indices and ecosystem vulnerability models to assess long-term environmental impacts.

Thus, the results obtained could not only serve as an example of a successful application of GIS and remote sensing in the context of military impact, but also form the basis for further systematic research on monitoring, environmental assessment, and restoration of affected areas in Ukraine.

References.

1. Savchuk, B., Stakhiv, I., Gordeev, A., Pastushenko, T., & Mironchuk, T. (2025). Impact of military operations on the fire status of lands in Kherson Region. *18th International Conference Monitoring of Geological Processes and Ecological Condition of the Environment, April 2025*, 1-5. Retrieved from https://www.earthdoc.org/content/papers/10.3997/2214-4609.2025510184

2. Pereira, P., Bašić, F., Bogunovic, I., & Barcelo, D. (2022). Russian-Ukrainian War Impacts the Total Environment. *The Science of the Total Environment, 837*, 155865. https://doi.org/10.1016/j.scitotenv.2022.155865

3. Rockström, J. (2024). Reflections on the past and future of whole Earth system science. *Global Sustainability, 7*, E15. Cambridge University Press. https://doi.org/10.1017/sus.2024.15

4. Roberts, J. F., Mwangi, R., Mukabi, F., Njui, J., Nzioka, K., Ndambiri, J. K., ..., & Balzter, H. (2022). Pyeo: A Python package for near-real-time forest cover change detection from Earth observation using machine learning. *Computers & Geosciences, 167*, 105192. https://doi.org/10.1016/j.cageo.2022.105192

5. Malenovský, Z., Rott, H., Cihlar, J., Schaepman, M. E., García-Santos, G., Fernandes, R. A., & Berger, M. (2012). Scientific requirements and challenges for the Sentinel-2 mission. *Remote Sensing of Environment, 120*, 71-90. https://doi.org/10.1016/j.rse.2012.01.021

6. Moffette, F., Alix-Garcia, J., Shea, K., & Pickens, A. H. (2021). The impact of near-real-time deforestation alerts across the tropics. *Nature Climate Change, 11*(2), 172-178. https://doi.org/10.1038/s41558-020-00956-w

7. Rawtani, D., Gupta, G., Khatri, N., Rao, P. K., & Hussain, C. M. (2022). Environmental Damages Due to War in Ukraine: A Perspective. *Science of the Total Environment, 850*, 157932. https://doi.org/10.1016/j.scitotenv.2022.157932

8. Klypa, A. V. (2024). The impact of military actions on natural ecosystems: consequences, rehabilitation, and an integrated approach. *Prostorovyi rozvytok*, (10), 471-481. https://doi.org/10.32347/2786-7269.2024.10.471-481

9. Bonchkovskyi, O., Ostapenko, P., Bonchkovskyi, A., & Shvaiko, V. (2025). War-induced soil disturbances in north-eastern Ukraine (Kharkiv region): Physical disturbances, soil contamination and land use change. *Science of the Total Environment, 964*, 178594. https://doi.org/10.1016/j.scitotenv.2025.178594

10. Hordiichuk, S., Chernov, A., Liashenko, D., & Stakhiv, I. (2024). Geoinformation Modelling of the Lower Dnipro National Nature Park Conditions as a Consequence of the Kakhovka Dam Destruction. *International Conference of Young Professionals "GeoTerrace-2024"*. https://doi.org/10.3997/2214-4609.2024510044

11. Lubin, A. S. (2019). Remote sensing-based mapping of the destruction to Aleppo during the Syrian Civil War between 2011 and 2017. *Applied Geography, 108*, 30-38. https://doi.org/10.1016/j.apgeog.2019.05.004

12. Stakhiv, I., Zatserkovnyi, V., De Donatis, M., Pastushenko, T., Hordiichuk, S., & Malik, T. (2025). Spatial analysis of the flooded land area of the Kherson Region Nature Reserve using remote sensing data. *Bulletin of Taras Shevchenko National University of Kyiv. Geology, 2*(109), 104-111. https://doi.org/10.17721/1728-2713.109.14

13. Tomchenko, O. V., Khyzhniak, A. V., Sheviakina, N. A., Zahorodnia, S. A., Yelistratova, L. A., Yakovenko, M. I., & Stakhiv, I. R. (2023). Assessment and monitoring of fires caused by the War in Ukraine. *Journal of Landscape Ecology, 16*(2), 76-97. https://doi.org/10.2478/jlecol-2023-0011

14. Tomchenko, O. V., Yakovenko, M. A., Stakhiv, I. R., & Liashenko, D. Y. (2023). Assessment of the quality loss, damage of forestry lands affected by military operations in 2021–2023. *GeoTerrace-2023*. https://doi.org/10.3997/2214-4609.2023510041

15. Shevchuk, S., Vyshnevskyi, V. I., & Bilous, O. (2022). The use of remote sensing data for investigation of environmental consequences of Russia-Ukraine War. *Journal of Landscape Ecology, 15*(3), 36-53. https://doi.org/10.2478/jlecol-2022-0017

16. Florath, J., & Keller, S. (2022). Supervised machine learning approaches on multispectral remote sensing data for a combined detection of fire and burned area. *Remote Sensing, 14*(3), 657. https://doi.org/10.3390/rs14030657

17. Kumar, N., & Kumar, A. (2020). Australian bushfire detection using machine learning and neural networks. *2020 7th ICSSS*, (pp. 1–7). IEEE. https://doi.org/10.1109/ICSSS49621.2020.9202238

18. Yang, S., Lupascu, M., & Meel, K. S. (2021). Predicting forest fire using remote sensing data and machine learning. *AAAI Conference on Artificial Intelligence, 35*(17), 14983-14990. https://doi.org/10.1609/aaai.v35i17.17758

19. Grari, M., Idrissi, I., Boukabous, M., Moussaoui, O., Azizi, M., & Moussaoui, M. (2022). Early wildfire detection using ML model deployed in fog/edge IoT layers. *Indonesian Journal of Electrical Engineering and Computer Science, 27*(2), 1062-1073. https://doi.org/10.11591/ijeecs.v27.i2.pp1062-1073

20. Mondal, M. S., Prasad, V., Kumar, R., Saha, N., Guha, S., Ghosh, R., Mukhopadhyay, A., & Sarkar, S. (2023). Multilayered Filtering Approach to Enhanced Fire Safety and Rapid Response. *Fire Technology, 59*(4), 1555-1583. https://doi.org/10.1007/s10694-023-01392-w

21. Mohanty, V., Behera, D. K., Panda, A. R., & Swetanisha, S. (2025). Comparative Analysis of Machine Learning and Deep Learning Models for LULC Classification Using Remote Sensing Data. *Indian Journal of Science and Technology, 18*(18), 1397-1409. https://doi.org/10.17485/IJST/v18i18.104

22. Ma, L., Liu, Y., Zhang, X., Ye, Y., Yin, G., & Johnson, B. A. (2019). Deep Learning in Remote Sensing Applications: A Meta-analysis and Review. *ISPRS Journal of Photogrammetry and Remote Sensing, 152*, 166-177. https://doi.org/10.1016/j.isprsjprs.2019.04.015

23. Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale Geospatial Analysis for Everyone. *Remote Sensing of Environment, 202*, 18-27. https://doi.org/10.1016/j.rse.2017.06.031

24. Congedo, L. (2021). Semi-Automatic Classification Plugin: A Python tool in QGIS. *Journal of Open Source Software, 6*(64), 3172. https://doi.org/10.21105/joss.03172

ГІС-оцінка впливу пожеж на ландшафти Херсонщини

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Мета. Розроблення методики моніторингу трансформації ландшафтів під впливом пожеж із використанням супутникових даних, мови програмування Python і геоінформаційних систем (QGIS) на прикладі Херсонської області. Основна увага приділена просторовій локалізації осередків займання, аналізу динаміки змін у структурі землекористування й виявленню екосистем, що зазнали найбільшого впливу.

Методика. У дослідженні використані методи дистанційного зондування Землі для виявлення й просторово-часової фіксації теплових аномалій і змін у земному покриві, геоінформаційні методи для інтеграції векторних і растрових даних, просторового поєднання шарів і класифікації землекористування, а також математичні й статистичні методи, зокрема нормування показників інтенсивності пожеж відносно площі адміністративних районів та аналіз їхньої динаміки. Для забезпечення відтворюваності розрахунків і автоматизації аналітичних процедур застосовані методи комп'ютерного моделювання із використанням мови програмування Python та SQL-запитів.

Результати. Реалізовано автоматизований підхід до просторової інтерпретації пожежної активності із класифікацією за типами угідь. За період 2021–2024 років виявлене суттєве зростання кількості пожеж, особливо у 2022–2024 роках. Найбільш вразливими виявилися лісові масиви, водно-болотні угіддя й урбанізовані території. Створено набір картографічних матеріалів, що відображають щільність пожеж за адміністративними районами з урахуванням типів землекористування. Просторовий аналіз підтвердив зв'язок між бойовими діями та зростанням інтенсивності пожеж на різних ландшафтах.

Наукова новизна. Розроблена методика автоматизованого моніторингу пожежної активності, що поєднує відкриті супутникові джерела (FIRMS, ESA), ГІС-інструменти (QGIS), мову Python і просторове нормування. Уперше запропоновано підхід, що дозволяє оцінювати динаміку змін у ландшафтах регіону внаслідок пожеж, ураховуючи категорії землекористування, адміністративні межі й щільність займання. Методика придатна для регіонального екологічного зонування та подальших системних досліджень.

Практична значимість. Отримані результати можуть бути використані для моніторингу екологічних наслідків бойових дій, формування стратегій післявоєнного відновлення, планування природоохоронних заходів, уточнення пріоритетних територій для розмінування й оцінки ризиків для населення. Методика забезпечує масштабованість, адаптивність і можливість її застосування в інших регіонах.

Ключові слова: *пожежі; дистанційне зондування Землі, геоінформаційні системи, ландшафтні зміни, супутникові дані, Python, QGIS, Херсонська область*

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