ISSN 2518-7325 (Online), ISSN 2306-1677 (Print)
Land Management, Cadastre and Land Monitoring
Received: 01.07.2026; Accepted: 26.08.2026; Published: 30.09.2026;
http://dx.doi.org/10.31548/zemleustriy2026.03.15

UDC 528.88:631.459]:623.4(477.52)

REMOTE SENSING AND GEOSPATIAL MODELING FOR DETECTION OF ABANDONED LAND USE SITES, DISTURBANCE AND LAND COVER DEGRADATION DUE TO THE WAR IN SUMY REGION OF UKRAINE: A SYSTEMATIC REVIEW

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Abstract. *The full-scale military invasion of Ukraine has caused multidimensional transformations of agricultural landscapes, land cover, and ecosystems. The Sumy region, located along the northeastern border with the russian federation, is a critical region that has suffered from intense fighting, prolonged artillery shelling, and ongoing border clashes during the study period from 2022 to May 2026. This article systematically evaluates the application of remote sensing and geospatial modeling techniques to detect, quantify, and monitor land abandonment, i.e., the withdrawal of such lands from active land use caused by the war, as well as physical land cover* *disturbances, chemical contamination, and broader environmental degradation. Combining recent scientific publications on the war in Ukraine and comparative global examples (Syria, Iraq, and Sudan), the effectiveness of integrating multi-sensor data, including optical (Sentinel-2, Landsat), synthetic aperture radar (SAR; Sentinel-1), thermal, and very high resolution (VHR; Maxar, WorldView) platforms, as well as advanced machine and deep learning algorithms (Random Forest, Deep Learning) and time series analysis (FANTA, two-period curve approximation), is assessed. The results of the study show that while geospatial modeling is an indispensable tool for rapid, large-scale, and non-contact damage assessment in conditions of active military conflict, significant critical research gaps remain, namely separating short-term cessation of agricultural use from actual withdrawal of such lands from active land use caused by war, verifying such facts in the face of a severe shortage of reliable ground data, and managing sensitive geospatial information. This systematic review highlights existing methodological gaps and outlines future prospects needed to build a harmonized spatial monitoring system capable of guiding post-conflict recovery and environmental remediation based on regional-scale remote sensing evidence.*

Keywords: *remote sensing; geospatial modeling; abandoned land; soil degradation; armed conflict; machine learning; land damage assessment.*

Relevance of the study. Conducting such a systematic review, based on the principles of open science, is a relevant task, since the large-scale damage, losses and further degradation of the landscapes of Sumy region as a result of military actions have led to a rapid increase in the number of both domestic and international scientific studies. The indicated works are based on different remote sensing methodologies and various approaches to geospatial modeling, therefore there is an urgent need for a single analytical structuring of the achieved results. A systematic review will allow to combine disparate data, identify methodological gaps and form a holistic scientific base necessary for further monitoring, damage assessment and development of strategies for restoring the region's ecosystems.

Analysis of recent research and publications. The scale of military operations following Russia's full-scale invasion of Ukraine in 2022 has led to unprecedented disruptions to agricultural infrastructure and ecological stability [21, 37]. Geographically located on the frontline of the north-eastern direction of the military conflict, Sumy region has experienced the consequences of traditional mechanized warfare, heavy artillery shelling, and changing dynamics of territorial control [11, 21]. This has led to mass abandonment of land plots, profound changes in physical cover, and significant land degradation in one of the most productive agricultural areas of Ukraine [6, 21].

Monitoring the environmental impacts of modern high-intensity warfare poses serious logistical and physical challenges. Direct field measurements and traditional soil mapping campaigns are often limited, highly dangerous, or completely prohibited by ongoing hostilities, active artillery threat vectors, and the ubiquitous presence of unexploded ordnance and landmines [5, 21]. In such conditions, remote sensing technologies and geographic information systems have moved from the role of auxiliary data streams to the main, and often the only, information source for rapid, large-scale, and continuous assessment of the state of the environment [19, 21].

Recent methodological advances have led to the deployment of diverse geospatial architectures adapted to conflict zones. Researchers have used a constellation of medium-resolution satellites (Landsat and Sentinel-2) combined with the synthetic aperture radar (SAR) from Sentinel-1 to assess vegetation dynamics and landscape structural changes [21, 23, 43] . Innovative algorithms, ranging from traditional machine learning classifiers such as Random Forest to sophisticated deep learning models (convolutional neural networks and Siamese neural networks), have been trained to detect small-scale landscape anomalies [7, 27, 44].

These geospatial tools are primarily aimed at quantifying such parameters as the cessation of the use of highly productive agricultural lands [11, 21]; physical microtopographic disturbances, such as cratering caused by explosive munitions, bombardment [7]; local and diffuse chemical contamination of soil with heavy metals and explosive residues [37]; and the destruction of natural objects, such as protective forest belts and natural water bodies [22, 39].

The main objective of this systematic review is to assess how remote sensing and geospatial modeling have helped to detect and map land abandonment, soil disturbance, and land degradation caused by war, with a focus on operational actions within the Sumy region during the period from 2022 to May 2026. This systematic review analyzes current technical trends, examines the empirical results achieved, identifies dominant methodological and systemic gaps, and suggests strategic directions for future research and planning for post-conflict land use restoration.

Materials and methods. A systematic review is a structured research method that identifies, critically appraises and synthesises available peer-reviewed evidence to answer a specific, well-defined research question. To prevent bias and manipulation of data during the process, a protocol outlining the full methodology is drawn up before the search begins. This protocol is publicly registered in the OSF database, ensuring that the principles of "open science" are adhered to [9]. This ensures that authors have not changed their criteria mid-process just to obtain the desired results. Systematic reviews are written and structured according to international standards, in particular the PRISMA declaration (Preferred Reporting Elements for Systematic Reviews and Meta-Analyses), such a checklist ensures that each stage of the review is fully transparent to reviewers and readers [33]. This systematic review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure transparent, objective, and reproducible synthesis of evidence. The PRISMA flowchart [26] was used to systematically document the study selection process, clearly describing the identification, screening, eligibility, and inclusion of all articles assessed. Google Bibliographic Search Services scholar and Consensus were used to search for key publications on the topic of this study. Consensus operates all available bibliographic databases, including Semantic Scholar, OpenAlex, PubMed, includes millions of scientific works, which also overlap with the Scopus and Web of Science databases, and in total has over 200 million peer-reviewed materials. Google was used to create graphic diagrams Notebook LM with infographic option.

Research results. The technical processes used for remote monitoring of land surface changes caused by war rely on a structured hierarchy of sensor data collection, signal processing, machine learning classification, and GIS-based multi-criteria spatial analysis. This multi-level architecture is designed to overcome data gaps caused by cloud cover, atmospheric interference, and the lack of systematic and up-to-date ground reference data [19, 23] . The basic configuration for landscape-scale assessment requires the integration of multiple remote sensing streams to capture different biophysical characteristics of the land surface [8, 23].

The scheme of combining these flows (Fig. 1) illustrates a complex algorithm for processing remote sensing data to obtain geospatial analytics. The process begins with the collection of information through heterogeneous sensors, including satellite optical and radar systems. The obtained data undergo the stages of cleaning from atmospheric interference and calculating specialized indices, such as the state of vegetation or the consequences of fires. Further, using machine learning algorithms and geospatial analysis, the system structures information for decision-making. The final step is a statistical check of the accuracy of the results, which confirms the reliability of the built model. This approach demonstrates the combination of innovative GIS methods for detailed monitoring of the earth's surface.

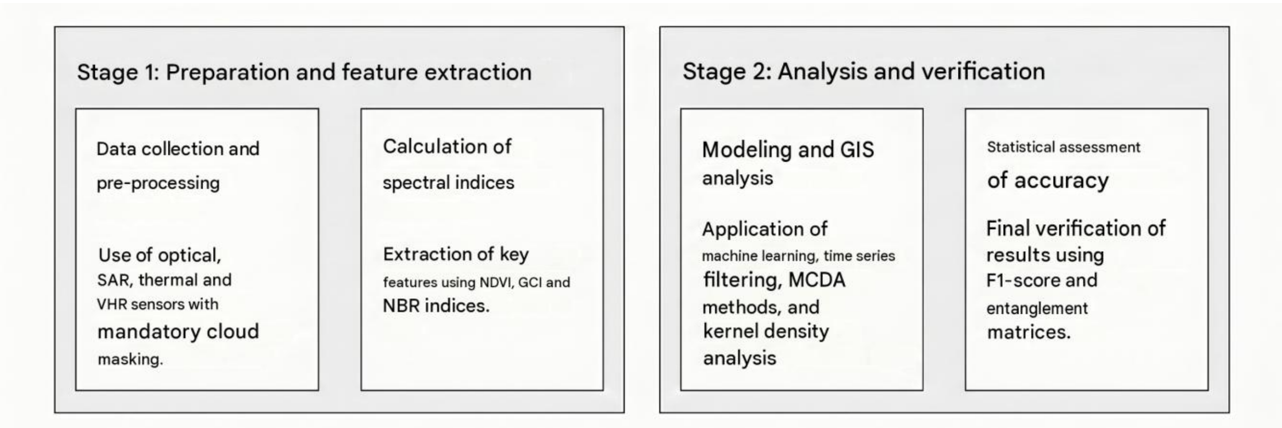

Fig. 1. Scheme of combining multiple remote sensing streams

Medium-resolution optical satellites Sentinel-2 (Copernicus) and Landsat 8/9 (USGS) provide the essential multispectral observations needed to monitor crop phenology, land cover, and overall vegetation health [1, 8, 21]. Using specific spectral bands, particularly the red-edge and near-infrared (NIR) regions, researchers calculate important vegetation metrics, such as the normalized difference vegetation index (NDVI), green chlorophyll index (GCI), and normalized burn rate (NBR), to detect field abandonment, vegetation reduction, and burn traces [1, 8, 21].

Synthetic Aperture Radar (SAR) Sentinel-1 C-band is integrated with optical data to provide all-weather, day and night observation capabilities [13, 23] . The SAR backscatter intensity and interferometric coherence metrics are highly sensitive to surface roughness, structural damage to built infrastructure, and changes in soil moisture, allowing continuous detection of land cover changes even during periods of heavy seasonal cloudiness in northern Ukraine [13, 23].

Thermal infrared sensors (TIRS) receive Thermal bands obtained from Landsat are used to derive land surface temperature (LST) models. Thermal anomalies help to assess soil moisture deficits and altered microclimates in areas of severely degraded landscapes [23].

Commercial sub-meter images from the Maxar, WorldView, and GeoEye satellite constellations are selectively used for targeted hot spot analysis [7, 17]. These resources are important for detecting and mapping individual, small-scale structural modifications such as military vehicle tracks, defensive trench systems, soil compaction zones, and isolated bomb or mine craters.

The transformation of raw spectral and radar backscatter data into practical land use maps involves careful time series reconstruction and machine learning algorithms [21, 23] . Time series smoothing and anomaly detection techniques are used for this purpose. To filter out noise from cloud cover and various atmospheric effects, multi-temporal optical datasets are pre-processed using advanced smoothing filters, such as the combined Gao and Savitsky-Goley filter method (GF-SG method) [21]. After smoothing, algorithms such as the Anomaly-Based Fallow Detection Algorithm (FANTA) are used to extract deviations in the expected growth profiles of agricultural land compared to historical baseline periods (2018–2021), allowing for the automated detection of fallow or completely uncultivated agricultural land [21].

Two-period NDVI and EVI curve fitting approaches track the temporal dynamics of agricultural plots during the growing seasons before and after conflict [8, 43]. Such mathematical modeling of agricultural lands allows us to distinguish fields that are completely unused (showing natural signs of weed/shrub succession) from fields that are simply left unattended or are being cultivated late due to logistical constraints of conflict [8, 43].

Random Forest algorithm (RF) dominates machine learning-based land cover classification processes due to its robustness to high-dimensional data and multicollinearity [19, 21]. RF models use an ensemble of decision trees trained on combined spectral bands, vegetation indices, and topographic variables, which consistently provides high macro-averaged classification performance in conflict-affected areas [1, 21].

Advanced semantic segmentation models, including convolutional neural networks (CNNs), are increasingly being used to capture spatial and contextual variations in high-resolution imagery [20, 27] for deep learning and data fusion for change detection. Context-aware smoothing and land-cover-aware data integration strategies combine Sentinel-1 and Sentinel-2 input data to remove background signal noise and improve the delineation of both structural damage and abrupt vegetation changes [15, 23]. The final classification vectors are integrated into a geographic information system (GIS) environment to produce actionable maps for decision support [21] .

Point data representing localized damage (e.g., shell craters, mines, or burned vegetation) are transformed into continuous surface models using Kernel Density Estimation (KDE) and hexagonal spatial binning grids [21]. This highlights regional clusters of degradation and tracks the spatial migration of frontlines over time.

Multi-criteria decision analysis (MCDA) is primarily represented by spatial optimization models that incorporate the Analytic Hierarchy Process (AHP), combining remote sensing layers with auxiliary variables such as soil type, proximity to military defense lines, and topography. This allows for the creation of land suitability maps and the identification of “risk actors” that warn of potential mine contamination or serious danger of topsoil degradation.

Model validation is performed using independent test sets divided into available ground data, historical reference registers, and comparisons with the United Nations Organization Satellite Centre (UNOSAT) damage archives [1, 19]. Standardized confusion matrices are generated to report overall accuracy, Kappa coefficients, and F1 coefficients, providing structural transparency and scientific validity [19, 21].

The application of remote sensing and geospatial architectures in Sumy region and wider Ukraine has provided a broad empirical understanding of the environmental consequences of the war that lasted from 2022 to 2026.

A summary of comparative data from the sources used for the systematic review is provided in Table 1.

Table 1. Summary of comparative data from sources used for the systematic review

Sensor/Methodology Category	**System/algorithm used**	**Primary application domain**	**Key quantitative outcome indicator**	**Sources**
Optical with medium resolution	Sentinel-2 / Landsat 8–9	Mapping of vegetation indices (NDVI, GCI, NBR)	Macroagricultural phenological trajectories	[1] Shelestov et al., 2022 [21] Yue-Wei Ma et al., 2022;
Synthetic aperture radar	Sentinel-1 C-band	Structural changes and monitoring in all weathers	Backscatter intensity and coherence offset (σ^0)	[23] Mhanna S. et al., 2023; [15] Karwowska et al., 2026
Very High Resolution (VHR)	Maxar / WorldView / GeoEye	Microtopographic identification of military traces	Number of craters, width of compaction track	[6, 7] Bonchkovskyi et al., 2025;

				Bonchkovskyi et al., 2023
Time series filtering	GF-SG filter	Data smoothing and cloud reconstruction	Reconstructed continuous NDVI profiles	[21] Yue-Wei Ma et al., 2022
Abnormal land use changes	FANTA Framework	Demarcation of fallow and unmanaged areas	Time deviation estimates	[21] Yue-Wei Ma et al., 2022
Machine learning with a teacher	RF algorithm	Multiclass land cover classification	Classification F1 scores (~0.83–0.87)	[1, 21] Shelestov et al., 2022 Yue-Wei Ma et al., 2022;
Spatial aggregation GIS	Core Density / Hexagonal Meshes	Regional clustering of degradation	Hotspot Density Maps / Risk Flags	[21] Yue-Wei Ma et al., 2022

Detecting and mapping war-induced land use neglect. Time-series analysis of satellite data has documented a significant, abrupt shift in agricultural operations since the start of the full-scale invasion in 2022 [11, 21] .

Spatial clustering and dynamics: The integration of FANTA algorithms and Random Forest classifiers revealed a sharp increase in the number of abandoned, uncultivated, and unharvested agricultural lands after 2022 [11, 21]. Geographically, such fields are not randomly distributed; instead, they exhibit intense spatial clustering within areas directly intersecting front lines, heavily fortified defense lines, and the immediate northern border zones of Sumy region [19, 43].

Classification performance: Random forest classification frameworks have achieved high performance in mapping these agricultural changes [1, 21]. Using integrated optical spectral bands and derived vegetation indices, these workflows have shown high classification performance, with F1 scores consistently ranging from ~0.83 to 0.87, and exceeding 0.90 in several optimized regional studies [1, 19, 21].

Typological differentiation: Two-period NDVI curve approximation methodologies successfully divided lands withdrawn from active land use into clear operational subcategories [8, 43]. The system effectively distinguished between "unused farmland," characterized by a complete absence of agricultural features and a rapid onset of natural weed or shrub succession, and "unmaintained farmland," where fields were sown but left unharvested or harvested with delay due to active local security threats [8, 43].

3.2. Quantification of physical soil disturbances

The physical impact of military operations on the soil cover of the Sumy region was characterized using ultra-high resolution spatial modeling, which revealed widespread mechanical degradation [6, 7].

Definition of the concept: *Bomb turbation* describes the severe disturbance of soil profiles, horizons, and local geomorphological structures caused by the detonation of explosive munitions, resulting in continuous mixing of the soil matrix, local compaction, and cratering.

Crater mapping and density tracking: Sub-meter VHR datasets (Maxar, WorldView) have helped identify and catalog hundreds of thousands of bomb and artillery craters in conflict-affected fields [6, 7]. This systematic identification has revealed extensive profiles of "bombturbation"—the structural upheaval and destruction of natural soil profiles caused by the impact mechanics of high explosives [7].

Secondary geomorphological and hydrological risks: In addition to the direct cratering, geospatial monitoring from 2022 to 2026 recorded ongoing secondary geomorphological changes [7]. Craters that remain untreated have been shown to undergo gradual micro-gully erosion and degradation, which destabilizes the surrounding topsoil layers, accelerates erosion processes, and significantly increases the spatial risk of encountering unexploded ordnance (UXO) during any subsequent return of agricultural facilities to the area [7].

Mechanized Compaction Profiles: By selectively extracting spectral indices sensitive to variations in topsoil density and surface moisture, researchers have successfully mapped extensive soil compaction networks [7]. Heavy military transport routes characterized by tracked armored vehicles and logistics convoys have caused severe structural destruction of soil macroaggregates, significantly reducing future moisture infiltration capacity and soil aeration in large arable land corridors [6, 7].

3.3. Assessment of chemical pollution and soil degradation

Linking damage maps obtained through remote sensing with targeted field campaigns has provided a clear understanding of the toxicological footprint left by intensive military operations [37, 38].

Localized heavy metal hotspots: Field sampling campaigns targeting specific target coordinates across projectile impact zones detected by remote sensing revealed alarming concentrations of toxic heavy metals in crater centers and immediately adjacent soils [7, 38]. Soil samples confirmed spikes in cadmium (Cd), copper (Cu), lead (Pb), and zinc (Zn) that directly correlated with the fragmentation pattern of the munitions, with localized concentrations sometimes exceeding national regulatory safety limits by up to 62 times [7].

Spatial characteristics of contamination: Comparative landscape modeling has shown a clear demarcation between the spatial effects of physical and chemical degradation [6, 25]. While mechanical disturbances such as soil compaction and cratering were widespread over large agricultural areas, extreme chemical contamination remained highly localized around specific detonation points and military defenses, rather than manifesting as diffuse contamination on a regional scale [7, 25].

Biological and functional decline: Laboratory analyses linked to geospatial metrics confirmed that these chemical anomalies, combined with high-temperature explosions, resulted in severe biological degradation of the soil system [36]. Impact areas demonstrated profound disruption of the soil microbiome, complete sterilization of beneficial microflora, and an immediate decline in overall soil fertility parameters that persisted for several seasons after impact [36, 38].

3.4. Wider impact on the environment and ecosystem

The impact of war-induced landscape degradation extends beyond individual agricultural lands, changing the regional ecological balance and protective infrastructure throughout the Sumy region [22, 36].

Destruction of forest shelterbelts: Remote sensing assessments using various sensors have documented severe damage to protective forest shelterbelts (windbreaks), estimating that approximately 18% of these critical linear forest stands in buffer zones of active conflicts have been degraded or completely destroyed [22]. This destruction deprives the landscape of vital protective functions, directly exposing vast areas of surrounding agricultural land to accelerated wind erosion, altered microclimates, and inexorable loss of topsoil moisture [22, 25].

Pyrogenic trends: Multi-temporal fire monitoring workflows using MODIS and Sentinel-2 thermal anomalies have revealed significant increases in both the frequency and spatial extent of landscape fires [40]. These fires, driven primarily by kinetic warfare, artillery strikes, and deliberate tactical arson, have burned across agricultural fields and natural forest stands, causing rapid vegetation loss and massive carbon release [40].

Hydrological changes: Spatial monitoring has also recorded significant changes in surface water hydrology and water security. Physical destruction of critical water management infrastructure, dams, and rural irrigation canals has led to localized flooding, uncontrolled water accumulation on agricultural plains, and structural contamination of local nature reserves and wetlands [39] .

Systemic decline in vegetation greenness: Regional time series assessments throughout the conflict period (2022–2026) show a generalized, sustained decline in integrated vegetation greenness indices (NDVI/EVI) in areas that experienced prolonged military presence, reflecting systemic, multi-year landscape degradation [37, 43]

Discussion. Empirical data accumulated between 2022 and 2026 indicate that remote sensing integrated with geospatial modeling provides an invaluable non-contact basis for monitoring environmental damage in conflict zones that are not subject to expansion [21, 23]. The implementation of multi-sensor data fusion models (optical, radar, thermal) successfully overcomes traditional monitoring bottlenecks such as persistent cloud cover or data gaps, providing continuous observations using radar backscatter analysis [23, 41]. Machine learning classifiers, in particular Random Forest architectures, have proven highly adaptable for mapping complex land-use changes when using dense multi-year time series [15, 19].

However, these technical advantages are offset by serious operational limitations. Although VHR platforms (Maxar, WorldView) offer excellent spatial resolution, necessary for the identification of individual microtopographic impacts, such as shell craters or heavy equipment tracks, their systematic deployment across entire regional administrative sectors (such as the entire Sumy region) remains severely limited by high commercial acquisition costs and narrow sensor coverage [6]. Furthermore, the accuracy of advanced machine learning models is reduced without adequate, continuous ground verification data. In conditions of active hostilities or high levels of mine contamination, collecting independent field samples for verification is practically impossible, forcing researchers to rely on remote proxies that introduce spatial uncertainties into the final classification results [11, 19].

A persistent methodological challenge in post-conflict remote sensing is the precise distinction between standard, planned agricultural cropping and true, war-induced structural land abandonment [8, 23]. Short-term spectral variations may appear identical when assessing a single-season crop failure or a standard rotational cropping cycle [8] . To overcome this risk of misclassification, recent techniques have successfully shifted towards multi-year phenological trajectory analysis combined with two-period curve fitting methods [8, 43].

By tracking a multi-temporal vegetation curve over a continuous three- to four-year period, these algorithms can distinguish authentic, long-term signs of neglect, evidenced by gradual overgrowth and the ongoing loss of regular cropping cycles, from temporary logistical pairings caused by short-term seed or fuel shortages [8]. However, achieving absolute classification accuracy requires the integration of supporting socio-economic datasets, such as localized rural population migration rates, indices of supply chain disruptions, and regional market accessibility models, which remain challenging to construct in the face of volatile conflict.

High-resolution spatial data that detail terrain changes, structural damage, and specific agricultural transportation corridors have dual-use characteristics; they can inadvertently provide tactical information about troop movements, fortification locations, or logistical vulnerabilities [19, 34]. Researchers therefore face the challenge of balancing scientific transparency with compliance of open access data with strict military operational security protocols, which often requires intentional degradation of spatial resolution or delays in the publication of sensitive geospatial results.

Major platform variations lead to gaps in data integration. Merging raw data streams between different processing systems, such as the migration of workflows between Google Earth Engine (GEE) and the Copernicus Data Space Ecosystem (CDSE), requires intensive cross-platform calibration to harmonize different sensor geometries, atmospheric correction models, and cloud masking procedures, which can lead to processing artifacts if not corrected [19].

The ecological transformations observed in Sumy Oblast reflect patterns documented in other major contemporary conflict zones [8, 23] .

Geospatial modeling applied to the Syrian armed conflict (e.g., the Orontes River Basin and Tartus Province) has demonstrated how prolonged military operations are causing massive deforestation, uncontrolled agricultural land abandonment, and severe landscape degradation patterns that reflect the loss of buffer strips and fields across Ukraine [8, 23, 41]. Similarly, satellite tracking in Sudan and Iraq has established a clear link between active kinetic warfare, subsequent refugee or internally displaced person (IDP) migrations, and immediate reductions in regional biomass, accelerated soil erosion, and structural changes in long-term land cover [2, 12, 28, 29]. These international parallels highlight that while local soil characteristics vary (e.g., the highly vulnerable fertile chernozem topsoil of Ukraine compared to the arid soil profiles of the Middle East), the basic geospatial methodologies required to track environmental degradation caused by war remain applicable worldwide [8, 23]. Future perspectives and strategic frameworks for restoration. To move from reactive damage mapping to proactive, evidence-based landscape restoration, the remote sensing community must focus on building integrated, automated spatial monitoring architectures [14] . The future restoration of valuable agricultural assets in Sumy Oblast requires the institutionalization of a harmonized national spatial database capable of automatically processing multisensor observations to create continuous landscape vulnerability maps.

By transforming raw data such as crater density layers, soil compaction vectors, and buffer strip degradation indices into spatial multi-criteria decision analysis (MCDA) pipelines, national planners can dynamically prioritize specific areas for humanitarian demining, mechanical subsoil restoration, and targeted ecological restoration [19, 43]. This automated integration provides the scientific basis needed to support international claims on ecological damage and optimize resource allocation for post-conflict landscape restoration [19, 37, 38].

Conclusion: Remote sensing technologies combined with advanced geospatial models provide an important, scientifically sound methodology for detecting, categorizing, and monitoring war-induced land abandonment, physical topsoil disturbance, chemical contamination, and broader ecosystem degradation in the Sumy region of Ukraine during the 2022–2026 conflict period. By combining multispectral optical imagery, all-weather SAR observations, and selective, very high-resolution commercial datasets with robust machine learning architectures (such as Random Forest and phenological curve time series filters), researchers can accurately capture landscape damage dynamics under high-hazard conditions that preclude standard field campaigns.

Although these geospatial systems demonstrate high classification efficiency and adaptability to many sensors, their operational integration continues to face significant challenges, among which we note the following:

- High financial and data coverage limitations associated with very high resolution (VHR) sensors with sub-1 meter resolution.
- It is a complex requirement to reliably decipher and distinguish between short-term agricultural land reclamation and structural neglect due to war.

•Serious shortage of ground-level reference data caused by active security threats and mine contamination.

•Critical ethical and national security responsibilities associated with the processing of sensitive dual-use spatial intelligence data.

Questions for Further Research: Future research efforts in the field of conflict-focused remote sensing and direct support for post-conflict ecological recovery should address several critical issues:

1. *Algorithmic Optimization:* How can transfer learning methods and synthetic data generation models be optimized to maintain high classification accuracy in active conflict zones where data can be safely collected for null-validation testing?
2. *Socioeconomic data fusion:* What are the most effective data fusion protocols for systematically integrating non-spatial socioeconomic variables (e.g., regional labor migration, agricultural input supply disruptions, local market collapse indices) directly into multispectral remote sensing models to improve the distinction between temporary mating and permanent neglect?
3. *National Monitoring Architectures:* How can Ukraine create a highly secure, automated, and legally standardized national spatial data monitoring system that successfully balances the requirements for open access for scientific restoration with the strict boundaries of military operational security?
4. *Long-term monitoring of soil restoration:* What specific spectral proxy indicators can be developed to monitor the multi-year chemical and biological restoration of soils affected by “bombardment” and heavy metal contamination, following tactical restoration measures?

Answers to these questions will improve remote sensing methodologies and provide the empirical data needed to guide large-scale ecological restoration and sustainable land management planning in post-conflict Ukraine.

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ДИСТАНЦІЙНЕ ЗОНДУВАННЯ ТА ГЕОПРОСТОРОВЕ МОДЕЛЮВАННЯ ДЛЯ ВИЯВЛЕННЯ ВИПАДКІВ ПОКИНУТИХ ДІЛЯНОК ЗЕМЛЕКОРИСТУВАННЯ, ПОРУШЕННЯ ТА ДЕГРАДАЦІЇ ҐРУНТОВОГО ПОКРИВУ ВНАСЛІДОК ВІЙНИ В СУМСЬКІЙ ОБЛАСТІ УКРАЇНИ: СИСТЕМАТИЧНИЙ ОГЛЯД

Анотація. *Повномасштабне військове вторгнення в Україну спричинило багатовимірні трансформації сільськогосподарських ландшафтів, ґрунтового покриву та екосистем. Сумська область, розташована вздовж північно-східного кордону з російською федерацією, являє собою критично важливий регіон, який постраждав від інтенсивних бойових дій, тривалих артилерійських обстрілів та постійних прикордонних зіткнень у досліджуваний період з 2022 по травень 2026 року. Дана стаття систематично оцінює застосування методів дистанційного зондування та геопросторового моделювання для виявлення, кількісної оцінки та моніторингу покинутості земельних ділянок, тобто виведення таких земель з активного землекористування, спричиненого війною, а також фізичних порушень ґрунтового покриву, хімічного забруднення та ширшої деградації навколишнього середовища. Поєднуючи останні наукові публікації щодо війни в Україні та порівняльні глобальні приклади (Сирія, Ірак та Судан), оцінюється ефективність інтегрування різносенсорних даних, що включають оптичні (Sentinel-2, Landsat), радіолокаційні системи із синтезованою апертурою (SAR; Sentinel-1), теплові та дуже високороздільні (VHR; Maxar, WorldView) платформи, а також передові алгоритми машинного та глибокого навчання (Random Forest, Deep Learning) й аналізу часових рядів*

(FANTA, апроксимація кривої з двома періодами). Результати дослідження показують, що хоча геопросторове моделювання є незамінним інструментом для швидкої, масштабної та безконтактної оцінки збитків в умовах активного воєнного конфлікту, зберігаються значні критичні пробіли досліджень, а саме відокремлення короткострокового припинення сільськогосподарського використання від фактичного виведення таких земель з активного землекористування, спричиненого війною, перевірку таких фактів за умови серйозного дефіциту достовірних наземних даних та управління чутливою геопросторовою інформацією. Цей систематичний огляд висвітлює існуючі методологічні прогалини та окреслює майбутні перспективи, необхідні для побудови гармонізованої системи просторового моніторингу, здатної керувати постконфліктним відновленням та екологічною ремедіацією на основі фактичних даних ДЗЗ у масштабі регіону.

Ключові слова: *дистанційне зондування; геопросторове моделювання; покитуті земельні ділянки; деградація ґрунтів; збройний конфлікт; машинне навчання; оцінювання збитків для земель.*