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Research Article

Geospatial Workflow for Mapping War-Related Environmental Degradation and Potential Public Health Risks in Ukraine

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Abstract

This article systematizes methods of geospatial analysis for mapping the geoecological consequences of armed conflict in Ukraine and considers their potential long-term implications for public health. The study focuses on the spatial distribution of environmental risks associated with landscape destruction and other forms of war-related territorial degradation. As a practical case study, it demonstrates the integration of open geospatial datasets, particularly Copernicus Sentinel-2 imagery, using the open-source QGIS environment and the Google Earth Engine cloud platform. The proposed workflow illustrates how raw geospatial data can be processed into a landscape degradation map suitable for preliminary environmental screening and decision support. Particular attention is also given to ethical requirements for the future integration of health-related spatial data, including spatial aggregation and patient de-identification.

Keywords: Geospatial analysis; Google Earth Engine; war-related environmental degradation; Sentinel-2; public health; remote sensing.

Key Points

1. This review presents a methodological framework for mapping war-related geoecological degradation in Ukraine using free and open-source geospatial tools.

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2. The study reviews major open geospatial data sources and demonstrates an integrated workflow based on QGIS and Google Earth Engine for monitoring landscape degradation in conflict-affected areas.
3. The study does not establish direct epidemiological cause-and-effect relationships between environmental degradation and health outcomes. Instead, it proposes a reproducible geospatial workflow for identifying war-related landscape degradation that may support future public health risk assessment.
4. The proposed workflow highlights the importance of spatial data aggregation and privacy protection when integrating environmental and health-related information for future medical-geographic research.

Introduction

The understanding that geographic location is fundamental to public health relies on the concept of spatial data dependence. This concept states that georeferenced information requires specific analytical methods (1). The relevance of this approach stems from the fact that environmental factors and disease patterns are not distributed uniformly across space. Instead, they tend to form spatial clusters that may indicate underlying environmental drivers of health risk.

In the context of the armed conflict in Ukraine, this concept becomes particularly important because warfare creates localized zones of environmental and epidemiological concern. Landscape degradation results from the destruction of industrial facilities, landmine contamination, and damage to critical infrastructure. The disruption of water supply systems and wastewater treatment facilities further increases potential risks to public health.

The historical foundation of spatial analysis in epidemiology dates back to Dr. John Snow's investigation of the 1854 cholera outbreak in London. By mapping disease cases, Snow identified a concentration of mortality around the Broad Street water pump, providing one of the earliest demonstrations of the value of spatial analysis in public health (2). His work showed that visualizing the geographic distribution of disease can reveal relationships that are often difficult to identify using conventional statistical summaries alone. It subsequently became one of the classical examples illustrating how spatial thinking can support evidence-based public health decision-making.

The field developed further through the emergence of landscape epidemiology and the work of Jacques M. May (1896–1975), who introduced an ecological perspective into medical geography and systematized the global distribution of diseases (3, 4). Contemporary medical geography increasingly integrates geospatial analysis with environmental sciences, epidemiology, and remote sensing. Modern developments, including artificial intelligence and big-data analytics, are likely to further expand the capabilities of disease mapping and environmental health research (5).

Human health is strongly influenced by the characteristics of the surrounding environment in addition to hereditary and individual factors. Environmental quality affects long-term exposure to chemical, biological, and physical hazards and therefore plays an important role in shaping population health.

Subject and Objectives

The aim of this article is to present an open-source geospatial workflow for identifying war-related landscape degradation and to demonstrate its application using publicly available geospatial data. Rather than establishing direct epidemiological causality, the proposed workflow provides a reproducible methodological framework that may support future environmental and public health assessments in conflict-affected regions.

As a practical illustration, the article presents a workflow for producing landscape degradation maps from freely available satellite data and open-source software. The emphasis is placed on making geospatial analysis accessible to specialists in environmental health, ecology, and public health who may have limited experience with GIS technologies.

Accordingly, the following sections introduce only those GIS concepts that are essential for understanding the proposed workflow and interpreting its results. The intention is not to provide a comprehensive introduction to geographic information systems but to explain the methodological principles required for applying geospatial analysis to environmental health research.

The use of open-source software and publicly available geospatial databases helps reduce the barriers between academic research and practical environmental monitoring, facilitating wider application of spatial analysis in public health and environmental management.

Conceptual Background

Geoecology is generally regarded as an integrative discipline that investigates the interactions between the abiotic components of the Earth's surface and biological communities within specific spatial structures or landscapes (6). The contemporary development of geoecology is closely associated with analysing anthropogenic impacts on global and local geosystems, thereby supporting environmental risk assessment and sustainable management strategies (7). Geographic information systems (GIS) have become one of the principal analytical tools in geoecological research because they enable spatial modelling of environmental processes and improve the assessment of environmental change driven by both climatic and anthropogenic factors (8).

To understand how geospatial methods contribute to environmental health research, it is also necessary to consider the conceptual foundations of medical geography (9). This discipline examines the relationships between place, environment, and human health while recognising that health outcomes are shaped not only by individual characteristics but also by the spatial context in which people live.

Medical-geographic studies commonly address several complementary perspectives:

- comparisons between neighbouring communities demonstrating substantial spatial variation in health outcomes;
- analysis of intra-urban inequalities linking local socioeconomic conditions with disease distribution;
- assessment of the long-term influence of early-life environmental conditions on adult health;
- spatial analysis of regional health surveys to evaluate environmental influences on population health;
- aggregation of small-area datasets to improve statistical reliability where local sample sizes are limited (10).

Within the context of the armed conflict in Ukraine, this conceptual framework must also incorporate conflict-specific determinants of health. These include direct consequences such as injuries and mortality, as well as indirect effects resulting from population displacement, disruption of healthcare systems, environmental contamination, and deterioration of living conditions. These interacting dimensions have been comprehensively discussed by Jayasinghe (11) and other authors.

Modern analytical approaches, including multilevel analysis, enable researchers to distinguish contextual effects associated with place from compositional effects related to characteristics of individuals. Consequently, contemporary medical geography increasingly regards geographic space not merely as a physical container of events but as an active component influencing health through environmental, social, and economic processes (9).

Recent developments demonstrate the rapidly expanding role of GIS in environmental health research. Spatial statistics such as Moran's I are widely used to identify clustering patterns of diseases, whereas Getis-Ord Gi statistics facilitate hotspot detection in studies of infectious diseases and environmental hazards (12). Environmental exposure assessment frequently employs interpolation methods such as IDW and Kriging, while healthcare accessibility is commonly evaluated using network analysis and service-area modelling. More recently, machine-learning approaches and near-real-time spatial analysis have begun to complement these traditional methods by supporting predictive environmental and epidemiological modelling.

Because the primary audience of this review includes public health researchers, environmental scientists, ecologists, and policy specialists who may have limited experience with GIS, the following sections briefly introduce several geospatial concepts that are essential for understanding the proposed workflow.

Spatial analysis primarily relies on two complementary models of geographic information: vector and raster data.

Vector data represent discrete objects using precise geographic coordinates and are therefore particularly suitable for mapping features such as healthcare facilities, roads, or administrative boundaries. Raster data divide geographic space into a regular grid of cells and are more appropriate for representing continuous environmental variables, including vegetation condition, land surface temperature, or atmospheric pollution (8).

Each mapped object is associated with an attribute table containing descriptive information. In environmental and medical applications, these attributes may include demographic characteristics, environmental indicators, infrastructure parameters, or health statistics. The integration of spatial location with structured attribute data transforms a digital map into an analytical information system that supports querying, statistical analysis, and spatial modelling (13).

One of the most common challenges encountered by new GIS users arises from differences in coordinate reference systems (CRS). Because geographic datasets may be created using different map projections, layers representing the same territory can appear spatially misaligned. Standardising all datasets within a common coordinate reference system before analysis ensures correct spatial overlay and reliable measurements of distances and areas (14).

Materials and Methods

Data Sources

Recent developments in geospatial analysis have been characterised by the rapid expansion of open-source software and openly accessible geospatial datasets. In response to these developments, the Open Source Geospatial Foundation was established. It serves as a base platform for modern GIS development and ensures open and equitable access access to spatial analysis technologies. Unlike closed commercial ecosystems, this organization operates as a global non-profit community. Since its founding in 2006, it has promoted the development and dissemination of environmental research tools (15). Its main activity is to ensure openness in software development processes. This makes tools accessible to scientists and public sector representatives regardless of project funding levels.

One of the most widely used open-source GIS platforms is QGIS is widely adopted due to its versatility (16). Alongside it, GRASS GIS develops as a fundamental tool for complex mathematical modeling and spatial analysis (17). Another system is gvSIG, which is widely used in the European scientific community (18). The efficiency of these software packages relies on specialized libraries. These libraries are often integrated even into commercial alternatives. A notable example is the GDAL (Geospatial Data Abstraction Library) (19), which serves as a universal tool for processing geospatial data.

Recent advances in cloud computing and artificial intelligence have further increased the accessibility of cloud-based geospatial platforms such as Google Earth Engine (GEE) (20). They require basic programming skills. However, they allow users to process huge satellite datasets remotely on a server via a web interface. This eliminates the need to install software on a local computer.

Web mapping is an important factor for publishing research results. Here, geoportals designed for publishing dynamic maps on the Internet hold key positions. An example is the https://ourworldindata.org/ website. Interactive visualization of environmental and medical-geographic data in user browsers is implemented through OpenLayers and Leaflet libraries, which have become industry standards. The use of OSGeo tools in environmental risk studies ensures methodology transparency and research reproducibility according to the principles of open science (21).

To analyze the impact of local conditions on health, researchers use open datasets. These repositories allow studies even in regions with limited access to local statistics. The Copernicus program and Sentinel satellite series serve as key tools for remote sensing. These satellites provide regular data on atmospheric conditions and vegetation cover. The use of vegetation indices, such as NDVI, helps assess urban greenness levels. This environmental characteristic has been associated with lower stress levels and reduced cardiovascular diseases among the population. Concurrently, Sentinel-5P sensors provide daily monitoring of nitrogen dioxide and other aerosol concentrations (22). This mapping is critical for assessing the risks of respiratory pathologies in industrial zones (23). The mapping of urban heat islands based on satellite data also deserves attention (24). Such microclimatic features, especially during summer heat, act as a major risk factor for acute cardiovascular diseases.

To analyze the impact of environmental factors, ecological data can be combined with demographic and medical indicators from national and global institutions. The World Health Organization provides access to statistical datasets on morbidity and mortality at national and regional levels through the Global Health Observatory platform. These data allow the construction of predictive models. For spatial analysis within countries, researchers often use the WorldPop resource, which offers high-resolution population density maps. Combining environmental workload data with population counts in specific grid cells allows researchers to calculate pollutant exposure. Consequently, this approach helps identify the most vulnerable population groups (25).

Infrastructure data from the global crowdsourcing platform OpenStreetMap serve as another important open source. This resource allows free use of vector data. These layers include the locations of transport routes, green spaces, industrial facilities, and hospitals. Such data are necessary to build transport accessibility models or analyze residential proximity to toxic emission sources. Using tools like QuickOSM in QGIS, a researcher can generate a base map of the study area in a few minutes. This process easily integrates volunteer geospatial data into an analytical system (26). It provides high detail even when official government maps are outdated or closed to the public.

Despite the potential of open resources, data quality and validity remain key challenges for the scientific community. When using volunteered information or satellite imagery, researchers must pay special attention to data relevance and spatial scale. Data collected at a global level do not always correctly reflect local conditions. A researcher must consider positioning errors and potential data incompleteness . This issue requires verification through comparison with several independent sources. Academic objectivity demands a critical approach to interpreting open-data results. Researchers must always state the limitations of their chosen methodologies (8).

Study Area

The area surrounding the town of Soledar (Donetsk Region, Ukraine) was selected as a representative case study illustrating the proposed geospatial workflow. This study area includes sections along the combat line of contact (LoC) as well as de-occupied territories in the northern, eastern, and southern regions of Ukraine (Figure 1). To define the specific research area, the study used vector layers of the frontline. These vector data were obtained from the KMZmap geoportal (27) and operational reports from the OSINT (Open Source Intelligence) communities.

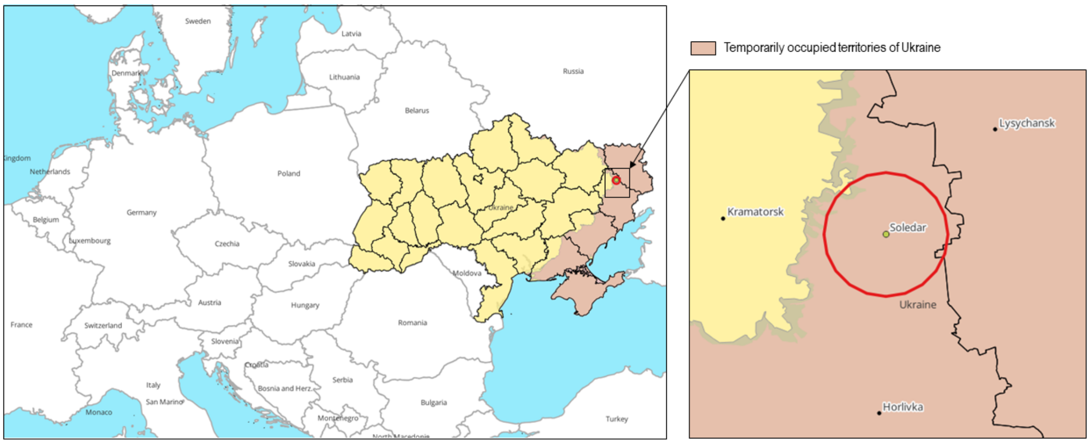

Figure 1. Study Area Location Map (Soledar town in the Donetsk region).

The study area comprises land plots, primarily arable lands, that currently suffer from damage and various types of pollution caused by explosions and mechanical destruction by heavy military machinery. The choice of this territory is driven by the high density of artillery and missile strikes. This intense bombardment has resulted in a cratered landscape (28), soil structure destruction, and large-scale forest fires (pyrogenic degradation). The territory of Ukraine is currently recognized as one of the most heavily mined in the world, with approximately 132,076 km2 remaining potentially dangerous (29). The presence of unexploded ordnance (UXO) makes classic field monitoring (ground-truthing) impossible, making remote sensing one of the few feasible approaches for environmental assessment under current conditions. Additionally, the environment is polluted by toxic residues of rocket fuel, heavy metals, and sulfur/nitrogen compounds due to ammunition detonations and oil depot fires. The territories adjacent to the line of contact (LoC) represent a zone of critical humanitarian and environmental disaster. Public health risks in these areas are driven by the contamination of underground and surface drinking water sources due to flooded mines and destroyed wastewater treatment plants. Furthermore, residents suffer from inhaling toxic dust and aerosols generated during active combat. Living amidst ruined communal infrastructure further intensifies long-term environmental stress on the human body through trophic chains, specifically via the consumption of contaminated local agricultural products.

Google Earth Engine Processing Workflow

To illustrate the proposed workflow for assessing natural and agricultural ecosystem degradation in the conflict-affected areas, an automated processing and integration of satellite imagery of satellite data was performed. To compare and detect changes in the land cover of the studied region, two temporal observation windows were established. The first period, from June 1 to August 30, 2021, was defined as the reference (baseline) period, reflecting the stable state of the territory. The second period, from June 1 to August 30, 2022, covers the phase of active hostilities and characterizes the direct military impact on geosystems. The choice of summer months eliminates the influence of seasonal vegetation phenology.

To illustrate the possibilities of rapid environmental warfare degradation assessment, this review paper utilizes the Google Earth Engine cloud platform. Google Earth Engine enables cloud-based processing of satellite imagery without requiring local storage or high-performance computing resources. This approach ensures data processing in key areas near the line of contact. The linear processing pipeline begins with calling a collection of atmospherically corrected Sentinel-2 imagery and applying spatio-temporal filtering based on the geometry of the area of interest for the periods of active combat. At the same stage, automatic artifact masking is performed using the built-in cloud quality control algorithm.

Based on the median composites of Sentinel-2 images for the summer periods of 2021 and 2022, differential vegetation indices (dNDVI) and burn indices (dNBR) were calculated within the Google Earth Engine (GEE) platform. These calculations used the spectral bands of the Sentinel-2 (Level-2A) MSI sensor according to baseline methodological specifications (30).

The threshold of dNDVI > 0.25 was established to isolate severe, non-seasonal vegetation loss and structural biomass degradation directly attributable to kinetic military impacts while filtering out minor phenological fluctuations (31). Concurrently, a dNBR > 0.3 parameter was applied to capture moderate-to-high burn severity and char exposure, successfully distinguishing pyrogenic combat scarring from mechanical land-cover disturbances.

To minimize spectral noise and exclude anthropogenic factors, a spatial mask of urbanized areas was applied to the resulting layers based on the European Space Agency (ESA) WorldCover 10 m dataset (32). Verification of the detected soil and vegetation destruction zones was carried out through spatial overlaying of thermal anomaly points from the NASA FIRMS service (33), that were used as a supporting spatial indicator of fire activity potentially associated with military operations. NASA FIRMS data were utilized as a visual raster overlay to corroborate the location of active fires with the detected zones of vegetative and structural damage. The proposed workflow is intended as a screening tool for identifying areas that may warrant more detailed environmental investigation rather than as a substitute for field verification where such verification becomes feasible.

Ethical and Privacy Framework

High-quality spatial data processing includes verifying geographic coordinates and unifying object identifiers based on the state Codifier of Administrative-Territorial Units and Territories of Territorial Communities (KATOTTH) (34). This approach allows the system to accurately link medical and environmental statistics with current settlement boundaries before loading analytical layers into the QGIS environment (8). The ethical and legal dimensions of the study require strict compliance with the balance between public benefit and individual privacy rights. This complies with the Law of Ukraine "On Personal Data Protection" (No. 2297-VI) (35) and the European General Data Protection Regulation (36).

Working with information in a military conflict zone creates additional risks. Precise mapping of the home addresses of patients or returnees planning to go back to de-occupied territories may lead to their de-anonymization. To prevent these threats, the study must apply the spatial data aggregation method (37) to the level of territorial communities or standardized grids with a cell area of no more than 1 km2. Additionally, a statistical masking standard ($n < 5$ rule) is implemented. According to this rule, any medical-geographic indicators in sparsely populated affected areas are automatically hidden if the number of potential subjects in a spatial cell is less than five people. Such precise information masking fully complies with international confidentiality requirements. Furthermore, it guarantees the security of sensitive public health data in the digital environment.

RESULTS

Open-Source GIS Workflow

As previously noted, the current stage of environmental, geographic, and medical-geographic research features the involvement of a wide range of specialists in mapping. QGIS serves as a convenient tool for this purpose. The software is well-suited for geo-analysis due to being entirely free and open-source. This allows scientists worldwide to utilize it without significant financial costs. The program is supported by a global developer community that constantly updates its functionality and creates specialized plugins. These tools are highly useful, particularly for analyzing data on territorial degradation and pollution. The use of open-source software guarantees the transparency of scientific methods and the reproducibility of research results. This factor is critical for public health publications (21).

To create high-quality visualization in QGIS, vector map formats are used. Unlike raster images, vector formats consist of separate objects whose display can be easily managed by changing colors or transparency. The structure of a vector map usually includes points, lines, and polygons grouped into different information layers. These layers range from natural boundaries to political-administrative divisions or built-up areas. The GeoPackage (*.gpkg) format is becoming the most popular standard in this field. Additionally, there are text formats based on markup languages, such as *.kml for three-dimensional modeling in Google Earth or *.geojson for rapid map visualization in web environments.

To solve specific analytical tasks, appropriate visualization techniques must be selected. Choropleth maps (38) allow the representation of territories using color shades based on the value of a relative indicator (e.g., disease cases per 1,000 population). Furthermore, dot density maps and dasymetric maps can be used to demonstrate the distribution of dispersed phenomena (38). Alternatively, the proportional symbol method (Fig. 2) can display localized data through marker placement and diameter (38). The generation of a geospatial database for medical infrastructure can be performed by filtering vector objects from the OpenStreetMap (OSM) crowdsourcing platform. The selection criteria relied on the presence of the base healthcare tag or corresponding values of the amenity attribute, namely: primary healthcare facilities and private practices (doctors), dental clinics (dentist), outpatient clinics (clinic), general hospitals (hospital), and pharmacies (pharmacy).

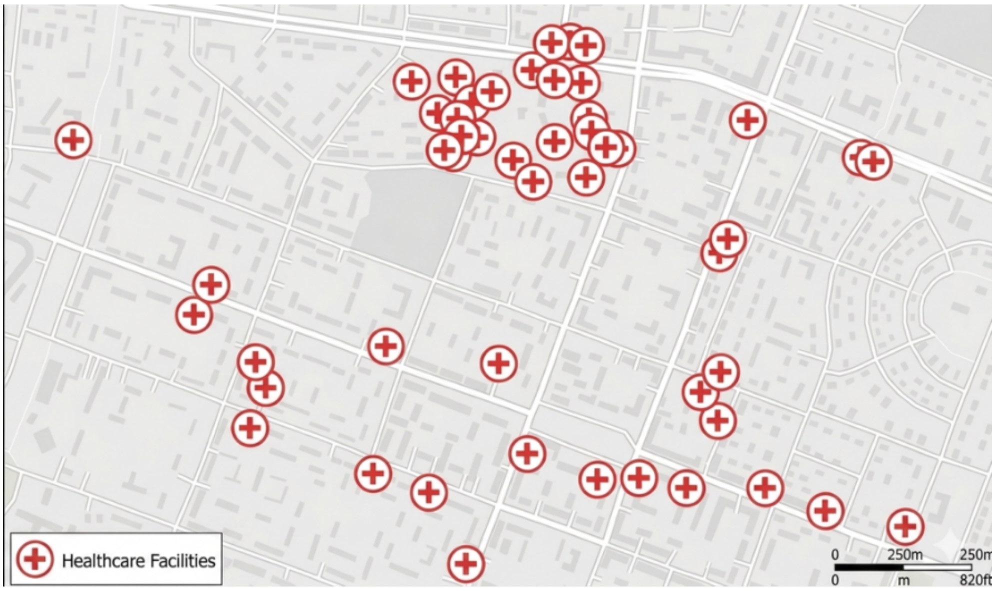

Figure 2. Medical infrastructure of the Horlivka city territory (fragment). Developed by the author based on data from (39).

Specialists often face the problem where disease distribution does not depend on administrative boundaries. Furthermore, a map can sometimes be overloaded with thousands of small objects, which hinders its readability. To display object density or phenomenon intensity without being tied to administrative borders, heatmaps or hexbins (Fig. 3) are used. Hexagonal binning (hexbins) divides space into equal hexagons, transforming chaotic points (such as patient addresses or infection outbreaks) into a structured matrix that is easy to analyze. Below is an example of the Ukrainian territory tessellation into 400-meter hexagons (40), within which population density is displayed. Such cellular structures allow for effective comparative analysis.

In medical cartography, legislation protects patients' personal data. Researchers are legally restricted from displaying the exact addresses (points) of individuals with conditions such as HIV, tuberculosis, or oncology on a map. Aggregating points into hexagons allows for the concealment of exact patient coordinates while preserving the spatial structure of an outbreak or cluster for ecological and medical analysis. A hexagonal grid closely replicates natural patterns and circular distribution ranges.

Furthermore, the human eye perceives hexagonal patterns much more easily than maps based on administrative divisions (Table 1).

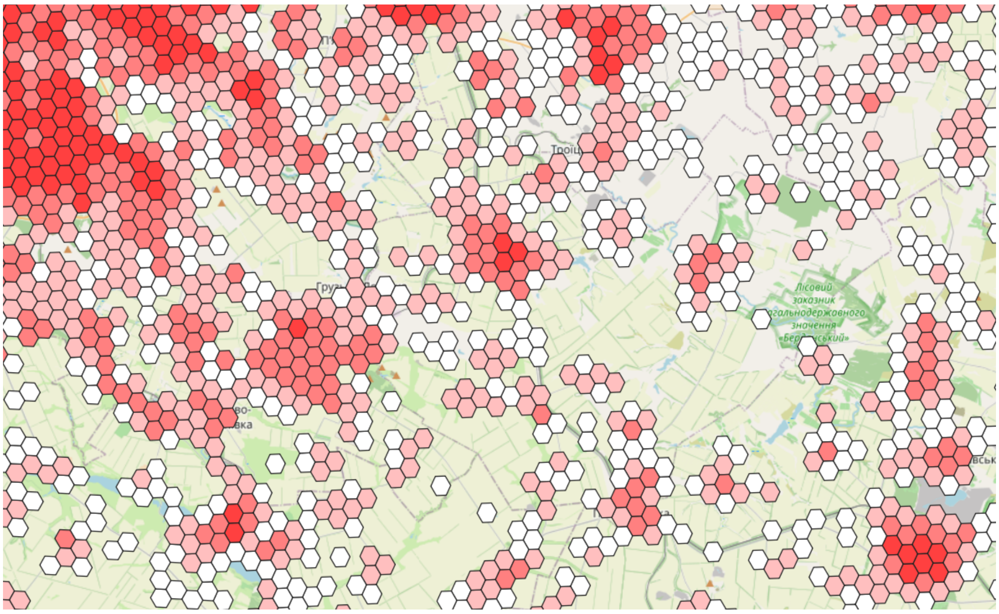

Fig. 3 Population density of the territory of Ukraine (fragment). Developed by the author based on data from (40).

Evaluation Criterion	**Administrative Division (Districts)**	**Hexagonal Grid (Hexbins)**
Area of Comparison	Variable (complicates data normalisation)	Identical (ideal for comparative analysis)
Cluster Localization Precision	Low (blurred/averaged across the entire district)	High (delineates outbreak boundaries)
Temporal Dynamics Analysis (Trends)	Complex (due to shifting administrative boundaries over time)	Stable (the grid configuration remains constant)
Personal Data Protection	High (at the expense of geographical precision)	Optimal (balances privacy requirements and spatial accuracy)

Table 1. Comparison of administrative boundaries and hexagonal bins as spatial data representation units.

It should be noted that for city-scale mapping (e.g., analyzing the accessibility of family doctors in Kyiv), hexbins with a radius of 500 meters or 1 km (walking distance) are ideal. For environmental epidemiology (e.g., the spread of Lyme borreliosis at a regional scale), a grid step of 5–10 km is preferred. If substantial territorial imbalances need to be demonstrated, special cartograms are applied, where the terrain contours themselves are deformed according to the variable values. Such visualizations can be created using professional open-source tools like QGIS or via specialized cloud services like Carto or Mapbox Studio. For final processing and color selection, specialists use auxiliary services such as ColorBrewer (41) or Mapshaper (42). The latter is an online tool developed by Matthew Bloch for editing vector formats (Shapefile, GeoJSON, TopoJSON, KML). In medical geography, it is most frequently used for the generalization (simplification) of administrative district boundaries. This reduces map file sizes for rapid loading in interactive dashboards while maintaining topological correctness without creating gaps between borders. The service also allows for rapid conversion between coordinate systems and attribute table editing.

The QGIS ecosystem owes its versatility to a modular architecture that allows functionality expansion through a plugin system. For healthcare and environmental specialists, this offers the possibility to transform a standard mapping program into a specialized research laboratory without the need for programming. The use of plugins significantly lowers the barrier to entry into the field of geospatial analysis. It automates complex data collection and processing operations that previously required substantial computational resources.

One of the most important extensions for rapid spatial information retrieval is QuickOSM (43). This plugin acts as a bridge between the researcher and the global OpenStreetMap database, allowing for the instant download of vector infrastructure datasets directly into a project. In medical and environmental studies, this enables the acquisition of up-to-date layers containing the locations of hospitals, pharmacies, industrial enterprises, or water bodies for a specific study area. This approach ensures high-speed cartographic base preparation and allows researchers to focus on risk analysis rather than the technical search for source files (44). Thus, the general algorithm for spatial visualization and basic analysis transforms digital datasets into maps that reveal the spatial distribution of phenomena (Figure 4).

The methodological workflow is structured into four sequential phases, aligning data acquisition with predictive spatial synthesis. The process begins by formulating a clear research hypothesis to guide the investigation; in medical geography and environmental epidemiology, this typically assumes a spatial relationship between landscape degradation and potential public health risks.

Phase 1 (Data Acquisition & Integration) focuses on collecting heterogeneous datasets to establish the study's baseline. Open-source geospatial infrastructure from OpenStreetMap provides foundational vector layers, while satellite imagery from the Copernicus Sentinel-2 platform delivers the core remote sensing data. Although real-time public health and demographic datasets (e.g., from PHC.org.ua or WHO) remain a critical data gap due to wartime constraints, baseline population density models are integrated during this step to narrow the high-priority screening areas. All disparate data streams undergo rigorous integration and harmonization to ensure spatial and attribute compatibility.

Phase 2 (Preprocessing & Indexing) transitions the raw data into analytical variables. Sentinel-2 imagery undergoes atmospheric correction, cloud masking, and temporal compositing to eliminate meteorological noise. This is followed by the calculation of differential spectral indices—specifically the Difference Normalized Difference Vegetation Index (dNDVI) and the Difference Normalized Burn Ratio (dNBR)—to quantify biophysical landscape degradation (45).

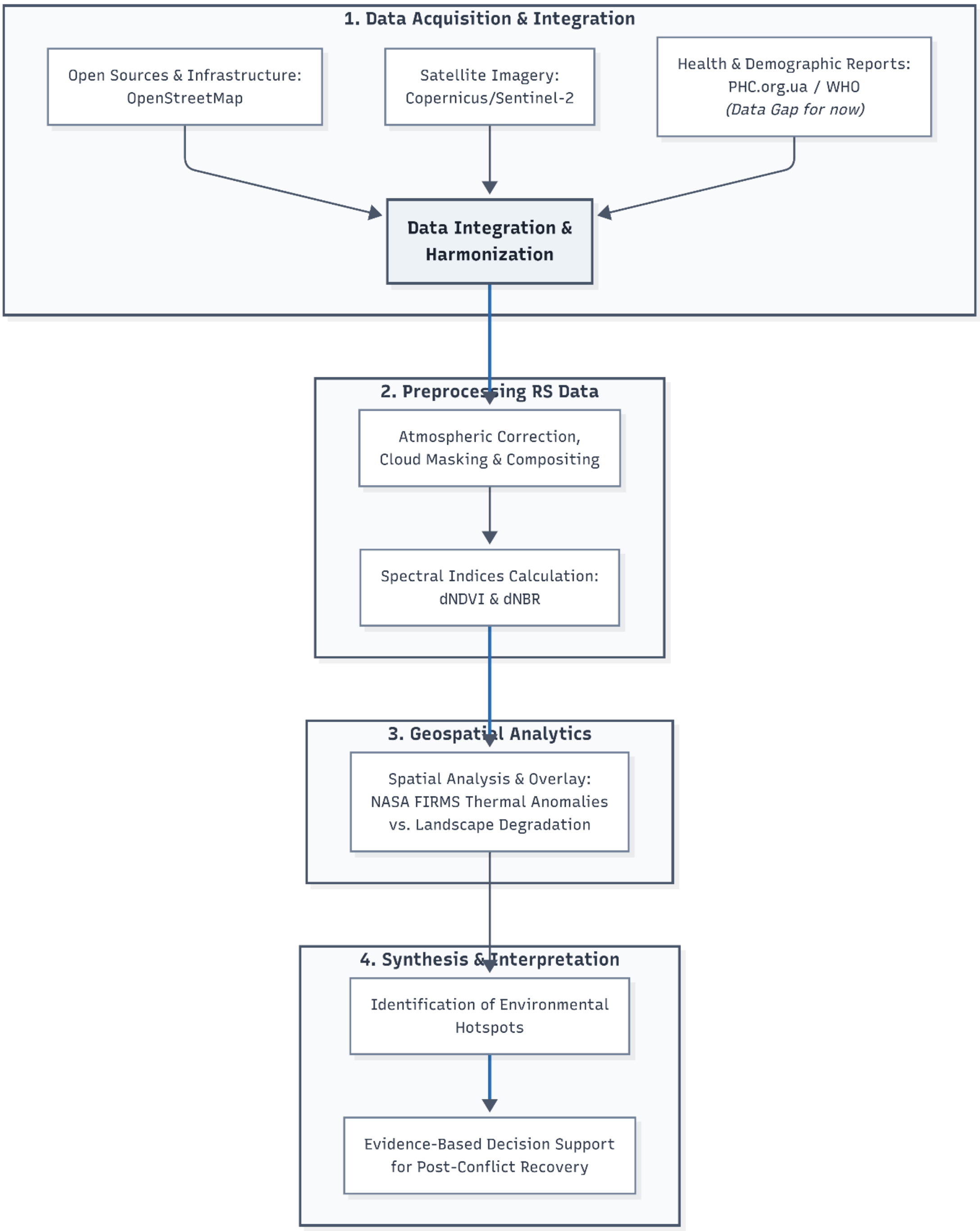

Figure 4. Case study spatial data visualisation workflow

Phase 3 (Geospatial Analytics) performs the core spatial modeling to reveal geographic patterns of the conflict's impacts (46). In this study, an overlay analysis is executed to cross-reference calculated dNDVI and dNBR degradation grids with independent active thermal signals from the NASA FIRMS dataset. Furthermore, the analysis integrates the geopolitical boundary data representing the line of contact at the end of 2025 using DeepStateMap.live tracking data (27). This multi-layer raster and vector overlay effectively delineates localized military impact zones and quantifies damage density.

Phase 4 (Synthesis & Interpretation) focuses on the identification of environmental and public health hotspots to generate actionable evidence-based decision support (13). While spatial overlap between high-density warfare degradation and potential risk zones provides strong visual validation of the initial hypothesis, the interpretation of these hotspots requires methodological caution. Direct epidemiological causation cannot be inferred solely from spatial proximity; confounding variables—such as socioeconomic disruption, forced migration, changing age structures, and fragmented healthcare accessibility—must be factored into future multi-criteria models (13). Ultimately, this phase transforms retrospective remote sensing metrics into a predictive framework, providing a robust decision-making tool for post-conflict environmental remediation and targeted public health strategies.

Landscape Degradation Case Study

Temporal change detection using the Google Earth Engine platform provided quantitative estimates of landscape degradation within the 15-km study area surrounding Soledar. During the active warfare phase in the summer of 2022, the integrated remote sensing algorithm identified a total of 9,989.37 hectares of severely degraded landscape. Concurrently, the independent NASA FIRMS dataset recorded an extensive footprint of thermal anomalies covering an aggregate area of 43,289.52 hectares within the same spatial boundaries (Table 2).

Metric Indicator	**Value (Hectares)**	**Spatial Proportion / Share**
Total Landscape Degradation (Sentinel-2)	9,989.37 ha	100.00%
Spatial Overlap with Thermal Events (FIRMS)	7,149.02 ha	71.57% (Verified Accuracy)
Non-Pyrogenic Structural Degradation	2,840.35 ha	28.43%
Reference Total FIRMS Anomaly Area (Buffered)	*43,289.52 ha*	—

Table 2. Summary of spatial comparison between Sentinel-2 landscape degradation and NASA FIRMS thermal anomalies

These quantitative estimates are intended to illustrate the practical application of the proposed workflow rather than to provide a comprehensive assessment of all forms of war-related environmental degradation within the study area. The observed spatial overlap suggests that most of the detected landscape degradation area was directly confirmed by independent thermal anomalies from the NASA FIRMS database. This correlation may demonstrate the dominance of the pyrogenic component in ecosystem destruction resulting from intensive artillery and missile strikes. The remaining degraded territory may also reflect military impacts that occurred without generating high-temperature thermal signatures detectable by satellite sensors (Fig. 5).

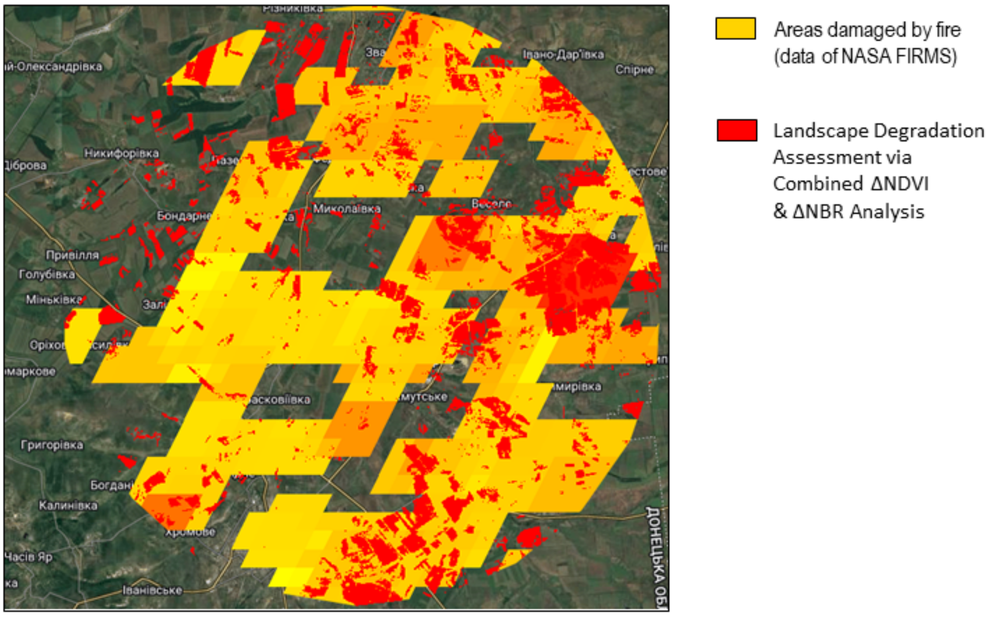

Figure 5. Integrated landscape degradation and thermal anomaly map of the Soledar study area. The visualization illustrates the spatial correspondence between Sentinel-2 vegetative/burn anomalies (9,989.37 ha) and independent NASA FIRMS fire footprints (43,289.52 ha). The 71.57% spatial intersection area marks the territories heavily impacted by war-induced pyrogenic degradation during the summer of 2022 relative to the 2021 pre-war baseline (47,48,49)

The significant discrepancy between the total area of thermal anomalies and the actual mapped landscape degradation is primarily driven by the spatial resolution of the sensors and the non-pyrogenic nature of specific military impacts. The substantial overestimation of the total FIRMS anomaly area, which reaches 43,289.52 ha compared to 9,989.37 ha of detected degradation, is a direct methodological consequence of the spatial coarseness of VIIRS and MODIS sensors. Even if a local sub-pixel thermal event occupies only a minor area on the ground, the system classifies the entire pixel as a thermal anomaly, artificially expanding the spatial footprint of the fire.

Conversely, the remaining 28.43 % of the identified landscape degradation, which lacks spatial intersection with FIRMS thermal points, results from non-pyrogenic, mechanical terrain transformations. This category encompasses structural disturbances that are not accompanied by open combustion or intense thermal radiation. Furthermore, this mismatch is amplified by the temporal revisit delay of the satellites. Short-term explosions or low-intensity fires could occur between the discrete sun-synchronous overpasses of the Suomi NPP and NOAA platforms. Consequently, they leave persistent physical and spectral degradation traces visible on high-resolution Sentinel-2 imagery while escaping real-time detection by thermal sensors.

The integration of such tools into the workflow provides the basis for developing of analytical models where satellite environmental data can be combined with detailed population distribution records. However, under wartime conditions, population data for these territories remain inaccessible. Thus, GIS serves as an essential tool for making informed decisions in environmental safety (8) and future healthcare management.

Public Health Risk Interpretation

It is hypothesized that environmental damage and territorial contamination may exert long-term adverse effects on public health, manifesting long after the cessation of active hostilities and during subsequent efforts to return these lands to economic use. The primary long-term threat stems from the chronic exposure of returning populations to heavy metals, chemical residues of explosives, and toxic combustion products that have infiltrated the soil and local aquifers. Consequently, the agricultural exploitation of these contaminated areas poses a direct risk of bioaccumulation, where hazardous substances enter the food chain through local crops and livestock. Similar pathways of exposure have been described in studies of post-conflict environmental contamination and military toxicology, although their magnitude depends on local environmental conditions and requires site-specific investigation. Furthermore, physical landscape disturbances during demining and soil reclamation can reactivate hazardous dust and particulate matter, leading to an increase in respiratory diseases and long-term carcinogenic risks among local workers and residents. Ultimately, these latent environmental hazards impose a persistent burden on the healthcare system, necessitating rigorous toxicological screening and spatial risk mapping prior to any socioeconomic recovery of the affected territories. The workflow presented in this study is therefore intended to support the prioritisation of environmental monitoring rather than to predict specific health outcomes.

Discussion

A fundamental challenge in interpreting spatial data regarding environmental and epidemiological conditions is the inherent risk of cartographic manipulation, where the selection of technical visualization parameters can drastically alter the perception of geographical reality. In the context of assessing warfare-induced landscape degradation and subsequent public health risks, suboptimal symbol sizing or inappropriate color ramp classification can artificially generate an illusion of an ecological catastrophe where none exists, or conversely, mask critical localized hazard hotspots. For instance, employing highly contrasting gradients for low-intensity disease incidence or minor vegetation index drops (dNDVI/dNBR) can provoke unsubstantiated public alarm. On the other hand, utilizing excessively large territorial units of analysis (such as aggregate regional boundaries instead of high-resolution hexagonal grids) tends to smooth out and obscure localized spikes in infections or toxic exposures. Consequently, researchers bear a profound ethical and methodological responsibility regarding data classification choices, as the visual clarity and cartographic integrity of the final map directly influence high-stakes administrative decisions in public health and ecological remediation strategies (50).

An important methodological aspect revealed by the model analysis of the Soledar territory—utilized in this review as a case study—is the significant spatial discrepancy between the NASA FIRMS datasets and the results of differential index (dNDVI/dNBR) calculations based on Sentinel-2 imagery. This phenomenon highlights a key limitation of relying exclusively on thermal anomalies to monitor warfare-induced destruction. Because the MODIS and VIIRS sensors possess low spatial resolution, a "sub-pixel exaggeration" effect occurs, where a localized fire event causes an entire pixel covering several hectares to be classified as a thermal anomaly. Conversely, integrating high-resolution Sentinel-2 data (10-20 m) allows for the verification of the actual boundaries of landscape destruction and filters out non-pyrogenic, mechanical damage, such as shell craters or infrastructural ruins that did not involve prolonged combustion. Consequently, for the purposes of medical and environmental monitoring, this review framework suggests employing cross-validation: FIRMS should serve as an indicator for the rapid detection of kinetic fire impacts, while differential remote sensing indices provide precise mapping of persistent ecological footprints and potential areas of toxicant bioaccumulation.

Within the framework of this review, the concept of environmental justice acquires a specific military dimension rooted in the critical asymmetry of geospatial data availability. Relying on crowdsourced platforms like OpenStreetMap (OSM) to map civilian and medical infrastructure introduces a distinct methodological pitfall: volunteer mapping activity naturally and sharply declines in close proximity to the line of contact due to life-threatening risks and communication infrastructure failures.

Consequently, the territories subject to the most intense military pressure – which require immediate medical and environmental assessment – risk becoming digital "blind spots." This data imbalance skews the overall perception of landscape and infrastructural degradation; while rear or socioeconomically resilient regions remain cartographically oversaturated, frontline communities suffer from data marginalization.

To uphold the principles of environmental justice, comprehensive monitoring frameworks must counteract this deficit. This can be achieved by integrating alternative, human-independent data streams, such as automated change detection via Sentinel-2 imagery and cross-verification through NASA FIRMS thermal anomalies, as demonstrated in the proposed algorithm.

Several systemic limitations inherent to the proposed review methodology must be acknowledged. First, the highly dynamic nature of military conflicts introduces a critical challenge regarding the lack of real-time demographic data. Relying on baseline population density models—such as Kontur 2023—remains inherently conditional; massive migration flows, forced evacuations, and the rapid depopulation of frontline urban areas drastically skew the actual spatial distribution of potential environmental risk recipients. Second, optical remote sensing via Sentinel-2 platforms is fundamentally constrained by meteorological conditions. Persistent cloud cover during periods of intense kinetic impacts creates data gaps, preventing the detection of the exact timing and immediate spectral signatures of landscape degradation. Furthermore, complex topographic features—particularly the unique anthropogenic terrain of the Donbas region with its numerous waste heaps and mine tailings—can generate false anomalies in vegetation index calculations due to shadow casting. These constraints underscore that the developed algorithm should be utilized as a primary tool for macro-scale screening, which requires subsequent validation through in-situ monitoring and field sampling of soil and water bodies once safety conditions permit.

Despite the noted limitations, the practical value of the proposed algorithm lies in establishing a predictive foundation for future toxicological monitoring and public health management in de-occupied territories. In the post-conflict period, comprehensive chemical analysis of soils and aquifers will be economically and logistically unfeasible due to the vast scale of contamination. The developed integrated GIS approach optimizes this process by shifting the paradigm from randomized sampling to targeted spatial screening.

Landscape degradation hotspots identified using hexbins and differential remote sensing indices will serve as high-priority zones for deploying mobile laboratories and conducting rapid screening for heavy metals and explosive residues. From the perspective of medical geography, this algorithm provides public health authorities with a tool for long-term epidemiological surveillance. By intersecting chronic environmental risk maps with future registries of patients returning to these lands, specialists will be able to proactively identify causal relationships between warfare-induced environmental destruction and the dynamics of oncological, respiratory, or endocrine pathologies—which is critical for formulating national security and ecological remediation strategies.

Future validation of this workflow will depend on the gradual availability of field observations, environmental sampling, and appropriately aggregated public health datasets in post-conflict settings.

Conclusions

This review demonstrates that the growing accessibility of open-source GIS and Earth observation data has substantially expanded the role of geospatial analysis in environmental health research. The principal contribution of this review is not the case study itself, but the presentation of a reproducible, openly accessible geospatial workflow that enables environmental health researchers without advanced GIS expertise to identify priority areas for future environmental and public health investigations in conflict-affected regions.

Lowering the technological barrier to entry into geospatial analysis has transformed mapping from an isolated engineering discipline into a versatile, cross-platform tool for scientific inquiry. The availability of open-source analytical software (15) and global Earth observation datasets has shifted the research focus from overcoming routine programming constraints to the substantive interpretation of environmental triggers and spatial-temporal disease patterns. This review demonstrates that for the context of Ukraine, cloud-based platforms—specifically Google Earth Engine—provide a secure, real-time, and operationally efficient framework for monitoring territories directly adjacent to the line of contact.

However, a significant gap remains between the technological potential of modern GIS and its practical implementation within public health decision-making. Most existing models are limited to the descriptive documentation of spatial patterns, such as mapping infrastructure destruction hotspots. Conversely, the causal mechanisms linking the synergistic factors of warfare-induced degradation (e.g., toxic dust, aquatic contamination, and pyrogenic burn scars) to the biophysical parameters of human health are frequently overlooked (46). Consequently, there is an urgent need to standardize integration protocols for clinical health data and spatial environmental variables at the intersection of human ecology, military toxicology, and medical geography.

The future development of environmental safety frameworks depends on transitioning from static landscape change analysis to predictive modeling. Promising research avenues include automating big data processing and integrating cloud-based machine learning algorithms via standardized plugins and web services tailored for non-GIS specialists, such as clinicians and ecologists. Progress in this domain requires establishing resilient interdisciplinary networks capable of combining geospatial landscape degradation indices with in-situ environmental quality metrics, disease incidence rates, and population migration dynamics. Rather than replacing conventional environmental or epidemiological investigations, the workflow presented in this review provides an accessible and reproducible framework for prioritising areas where detailed field studies and public health investigations are likely to have the greatest practical value.

Conflict of Interest

The authors declare no conflict of interest.

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Data Availability Statement

This study used publicly available secondary geospatial datasets. No individual-level health data were collected or processed. Derived geospatial layers were generated from Sentinel-2, ESA WorldCover, and FIRMS data for illustrative methodological purposes.

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