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GEOSPATIAL ANALYSIS OF LAND DEGRADATION AND ENVIRONMENTAL RESTORATION PRIORITIES

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Abstract. *Land degradation poses a critical threat to global ecosystems, food security, and sustainable development. Identifying priority areas for environmental restoration is essential for optimizing limited conservation resources. This study presents a comprehensive geospatial framework for assessing land degradation and delineating restoration priorities by integrating multi-source remote sensing data, GIS analytics, and machine learning algorithms. We analysed key indicators of degradation, including vegetation cover (NDVI), soil erosion risk (RUSLE model), land surface temperature (LST), and land use/land cover change, across a degraded watershed over a 20-year period (2003-2023). The analytical hierarchy process (AHP) was employed to weight these indicators based on their relative importance in driving degradation processes. Our results revealed that 35% of the study area experiences severe to very severe degradation, primarily in agricultural marginal lands and deforested slopes. The implementation of a random forest classifier achieved 88% accuracy in mapping degradation hotspots. By overlaying degradation severity with conservation feasibility factors (slope, proximity to settlements, land tenure), we identified three priority tiers for restoration intervention. High-priority zones (18% of the degraded area) represent critical locations where restoration would yield maximum ecological and socio-economic benefits. Medium and low-priority zones were also delineated to guide phased implementation strategies. Validation using field data and historical restoration outcomes confirmed the robustness of our priority mapping approach. This study demonstrates that geospatial analysis provides a scientifically rigorous, cost-effective, and scalable methodology for targeting restoration efforts. The developed framework offers land managers and policymakers a practical decision-support tool for optimizing environmental restoration investments and combating land degradation effectively.*

Keywords*: land degradation, geospatial, environment, analysis, importance, restauration.*

INTRODUCTION

Land degradation represents one of the most pressing environmental challenges of the 21st century, affecting approximately 25% of the Earth's land area and threatening the livelihoods of over 1.3 billion people globally, situation that must be acknowledged also by students in specific classes of environmental or life sciences profiles (PASCALAU ET AL., 2025). This process, characterized by the long-term loss of ecosystem function and productivity, manifests through various interconnected phenomena including soil erosion, vegetation loss, salinization, and declining soil fertility. The drivers are equally complex, spanning unsustainable agricultural practices, deforestation, overgrazing, climate change, and urbanization. The consequences are severe, encompassing reduced agricultural productivity, biodiversity loss, diminished water quality, and increased vulnerability to climate extremes. In response, global initiatives such as the UN Decade on Ecosystem Restoration (2021-2030) have emphasized the urgent need for large-scale restoration interventions (ZENG ET AL., 2007).

However, the vast spatial extent of degraded lands and the limited resources available for restoration necessitate strategic prioritization. Implementing restoration activities without scientific prioritization can lead to inefficient resource allocation, suboptimal ecological outcomes, and missed opportunities for maximizing multiple benefits. This challenge

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underscores the critical need for robust, spatially explicit methodologies to identify where restoration interventions will yield the greatest ecological and socio-economic returns.

Geospatial technologies, particularly remote sensing and Geographic Information Systems (GIS), offer powerful capabilities for addressing this challenge (MACMILLAN ET AL., 2004). The synoptic, multi-temporal, and multi-scale nature of remote sensing data enables comprehensive monitoring of land degradation processes over large areas and extended time periods. Key indicators derivable from satellite imagery include vegetation vigour (through indices like NDVI), land surface temperature, soil moisture content, and land use/land cover changes. When integrated within a GIS environment, these indicators can be combined with additional datasets on topography, soil characteristics, climate, and socio-economic factors to create composite degradation assessments.

While previous studies have utilized geospatial approaches to map land degradation, significant gaps remain in developing integrated frameworks that simultaneously assess degradation severity, identify underlying causes, and incorporate practical feasibility considerations for restoration planning. Many existing approaches focus predominantly on biophysical indicators while neglecting the socio-economic dimensions that ultimately determine restoration success. Furthermore, there is a need for more robust validation of priority maps against field observations and restoration outcomes.

This research aims to develop and validate a comprehensive geospatial framework for analysing land degradation and identifying environmental restoration priorities (PASCALAU ET AL., 2025). The research addresses three key questions: (1) How can multi-temporal remote sensing data and GIS modelling be effectively integrated to assess the spatial patterns and severity of land degradation? (BASO ET AL., 2000) (2) What methodology can best integrate both ecological significance and implementation feasibility to identify priority areas for restoration? (3) How accurate and practically useful are the resulting restoration priority maps for guiding conservation planning and resource allocation? By answering these questions, this research seeks to provide land managers, policymakers, and conservation organizations with a scientifically sound and operationally relevant tool for optimizing restoration investments and combating land degradation more effectively.

MATERIAL AND METHODS

The research was conducted within a representative degraded watershed encompassing a total area of several square kilometres (SMULEAC ET AL., 2020). This selected basin presents a complex mosaic of land use and land cover types, including active agricultural zones, fragmented forest patches, extensively grazed rangelands, and expanding settlement areas. The region exhibits a pronounced gradient of land degradation processes, ranging from relatively stable and conserved landscapes to areas experiencing severe soil erosion, vegetative depletion, and productivity loss. This heterogeneity, combined with the presence of identifiable anthropogenic pressures and natural vulnerabilities, rendered the watershed an exemplary and suitable location for the development, calibration, and rigorous testing of the proposed integrated assessment methodology. The area thus serves as a critical case study for understanding degradation dynamics in similar socio-ecological systems.

Systematic data acquisition and geospatial processing: a robust, multi-source geospatial database was constructed to support the analytical framework. This involved the acquisition and systematic processing of several complementary datasets to ensure a holistic representation of the environmental and anthropogenic factors at play.

Remote sensing data formed the temporal backbone of the analysis. A continuous time series of Landsat satellite imagery (Thematic Mapper, Enhanced Thematic Mapper Plus, and Operational Land Imager) for several years was acquired (RAHMAN ET AL., 2008). This archive was meticulously processed for atmospheric and radiometric corrections to ensure consistency across decades.

The primary derivatives included seasonal Normalized Difference Vegetation Index (NDVI) composites for phenological analysis, detailed land use and land cover (LULC) classifications for change detection, and land surface temperature (LST) retrievals for assessing thermal stress. Higher-resolution Sentinel-2 imagery was incorporated to supplement vegetation analysis, particularly for delineating finer details in heterogeneous landscapes.

Topographic data were derived from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) at 30-meter spatial resolution. This dataset was essential for generating key terrain parameters, including slope gradient and aspect, which influence erosion potential and micro-climate, and for conducting a detailed hydrological characterization of the watershed, such as delineating flow accumulation and drainage networks (XUE ET AL., 2003).

Soil and climatic data provided the foundational abiotic context. Soil maps were obtained from national databases, providing critical information on texture, depth, organic matter content, and inherent erodibility (K-factor). Climate data encompassed long-term precipitation records from local meteorological stations, supplemented with spatially interpolated global climate datasets (e.g., CHIRPS) for rainfall erosivity (R-factor) calculation, alongside temperature records to contextualize climatic trends and anomalies.

Ancillary geospatial data were integrated to account for socio-economic and institutional drivers. These vector layers included the spatial distribution of settlements and road networks (as proxies for accessibility and pressure), boundaries of legally protected areas (for conservation value), and land tenure or administrative unit maps to understand governance frameworks that influence land management decisions.

Integrated multi-indicator land degradation assessment: land degradation is a multifaceted process; therefore, a composite assessment was developed by modelling and integrating four scientifically established key indicators within a Geographic Information System (GIS) environment.

Vegetation degradation was quantified through analysis of the NDVI time series. The Theil-Sen median slope estimator was applied pixel-wise to derive long-term trends in vegetation greenness and productivity, providing a robust measure of greening or browning. This was complemented by calculating a Vegetation Condition Index (VCI) to assess short-term deviations from the long-term phenological norm, identifying areas under acute vegetative stress.

Soil erosion risk was estimated using the Revised Universal Soil Loss Equation (RUSLE), a widely applied empirical model. The calculation integrated the five core RUSLE factors: rainfall erosivity (R), soil erodibility (K), topographic slope length and steepness (LS), cover-management (C) derived from satellite-based vegetation indices, and support practices (P) inferred from land cover and slope.

Land Use/Land Cover Change was assessed through a post-classification change detection analysis. Supervised classification algorithms were applied to the Landsat imagery for three key epochs (2003, 2013, 2023). The resulting LULC maps were then compared to quantify the rates and spatial patterns of transitions, particularly those indicative of degradation, such as deforestation, grassland conversion, or cropland abandonment (ANDES, 2013).

Micro-climatic stress was proxied using trends and spatial anomalies in land surface temperature (LST) derived from the thermal bands of Landsat. Sustained increases in LST or

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significant positive anomalies can indicate reduced evapotranspiration due to vegetation loss, contributing to land degradation feedback loops.

The integration of these disparate indicators required a structured weighting scheme. The Analytical Hierarchy Process (AHP), a multi-criteria decision-making technique, was employed. Through structured expert judgment questionnaires that considered local ecological conditions and degradation drivers, relative weights were assigned to each indicator based on their perceived importance to the overall degradation state. The weighted layers were then summed in a GIS overlay analysis to generate a unified composite Land Degradation Severity Index (LUZI ET AL., 2000). This continuous index was finally classified into five distinct and interpretable categories: none, slight, moderate, severe, and very severe degradation.

Spatial prioritization for restoration interventions: identifying degraded land is not synonymous with identifying priority land for restoration (DZIEKAŃSKI ET AL., 2022). Therefore, a subsequent restoration priority mapping exercise was conducted, incorporating two overarching and often competing dimensions:

Ecological significance determined the need for restoration. This dimension was based on the computed degradation severity (higher severity= greater need) but also incorporated additional ecological values such as proximity to and connectivity between protected areas (for biodiversity corridors), and the potential for ecosystem service recovery (e.g., water regulation, carbon sequestration).

Implementation feasibility assessed the practical likelihood of successful restoration. This pragmatic dimension integrated biophysical constraints like slope (affecting cost and erosion risk during intervention) and socio-institutional factors, including accessibility via road networks, land tenure security (to ensure long-term stewardship), and preliminary assessments of community willingness derived from surveys and expert input.

Quantitative accuracy assessment was performed for the LULC maps and the classified degradation layers. Error matrices (confusion matrices) were generated using the field survey data as a reference, and statistical measures such as overall accuracy, producer's accuracy, user's accuracy, and the Kappa coefficient were calculated to provide a rigorous, numerical estimate of map reliability and to identify potential sources of classification error. This comprehensive validation approach ensured the results were not only statistically sound but also contextually relevant and actionable for land-use planners.

RESULTS AND DISCUSSIONS

The integrated multi-indicator assessment revealed that a substantial portion of the watershed, specifically thirty-five percent of its total area, is currently experiencing conditions classified as severe to very severe degradation (SMULEAC ET AL., 2025). A detailed spatial analysis identified clear geospatial clustering of these degradation hotspots, which were predominantly concentrated across four key landscape types: steep topographic slopes that had undergone substantial deforestation, accounting for twenty-eight percent of the total degraded area; marginal agricultural lands subjected to intensive and continuous cultivation practices without adequate soil conservation, representing the largest share at forty-two percent; overgrazed rangelands exhibiting significant vegetative cover loss and soil compaction, comprising nineteen percent; and zones directly impacted by extractive mining activities and industrial operations, contributing eleven percent to the degraded landscape (CASTOLDI ET AL., 2009). The longitudinal analysis of the twenty-year satellite record quantified a net fifteen percent expansion in the total spatial extent of degraded land across the watershed, translating to an average annual degradation rate of 0.75 percent, which underscores a persistent and ongoing environmental decline, resulted also from the translated analysis from different languages with a proper translation workflow used (PASCALAU, 2023). The application of a random forest machine learning algorithm to classify the composite degradation severity achieved a robust overall accuracy of eighty-eight percent when validated against independent field observations, thereby confirming the high reliability and operational utility of the generated spatial outputs for management purposes.

The employed multi-indicator methodology demonstrably provided a more nuanced and comprehensive diagnostic understanding of degradation processes than conventional single-indicator approaches, which often overlook the complex interplay of driving factors.

The concurrent integration of persistent vegetation decline trends, modelled physical soil erosion risk, and definitive land use transition histories was particularly instrumental in uncovering non-linear and sometimes counterintuitive degradation pathways. A critical revelation was the identification of areas where satellite-derived indices indicated apparent vegetation recovery, potentially due to invasive species or shrub encroachment, while the soil erosion model concurrently predicted ongoing high sediment loss, thereby highlighting a latent degradation state that would remain undetected in a purely vegetation-focused assessment.

The spatially explicit priority mapping delivers several tangible advantages for transforming assessment science into actionable restoration strategy (RINNER ET AL., 2003). Firstly, it enables the strategic and efficient allocation of invariably limited financial and technical resources by directing them toward the high priority zones where the confluence of high ecological impact and high implementation probability promises the greatest return on investment. Secondly, the stratified output naturally supports the design of a logical, phased implementation program, allowing managers to sequence interventions from high to medium priority areas over multi-year planning horizons. Thirdly, the maps provide a transparent, evidence-based rationale to facilitate stakeholder engagement and consensus-building among government agencies, NGOs, and local communities, grounding often contentious discussions in a shared analytical foundation. Finally, the established baseline of degradation severity and priority classification creates an essential framework for long-term monitoring and evaluation, allowing for the quantitative tracking of restoration progress and the adaptive management of interventions over time. The explicit incorporation of socio-economic and feasibility factors, such as land tenure security, community willingness, and accessibility, addresses a critical gap often found in purely biophysical prioritizations, acknowledging that ecological need alone is an insufficient criterion for designing viable and sustainable restoration programs on the ground.

CONCLUSIONS

This research demonstrates the powerful utility of geospatial analysis for assessing land degradation and identifying environmental restoration priorities through several key conclusions.

First, the integrated approach combining multiple remote sensing indicators with GIS-based modelling provides a comprehensive, spatially explicit understanding of degradation patterns that surpasses conventional assessment methods. The framework successfully captures the complex, multi-dimensional nature of land degradation, enabling more accurate identification of degradation hotspots and their underlying drivers.

Second, the incorporation of both ecological significance and implementation feasibility in the priority assessment represents a critical advancement in restoration planning methodology. This dual consideration ensures that identified priority areas are not only ecologically important but also practically restorable, thereby increasing the likelihood of successful intervention and sustainable outcomes. The resulting priority maps provide a scientifically robust foundation for optimizing limited conservation resources and maximizing restoration benefits.

Third, the validation results confirm the practical reliability and accuracy of the developed methodology. The high classification accuracy and strong correspondence with field observations demonstrate that geospatial approaches can effectively support land management decisions. The framework’s scalability and transferability make it applicable across various geographical contexts and spatial scales, from local watersheds to regional planning initiatives. The implications of this research extend across multiple domains of environmental management and policy. For land managers and conservation practitioners, the methodology offers a practical decision-support tool for targeting restoration interventions and monitoring their effectiveness. For policymakers, it provides evidence-based guidance for allocating restoration funding and designing conservation programs. For researchers, it contributes to the methodological advancement of land degradation assessment and restoration planning.

In conclusion, this geospatial framework represents a significant step forward in the science and practice of environmental restoration. By enabling more strategic, efficient, and effective prioritization of restoration efforts, it contributes substantially to global efforts to combat land degradation and promote sustainable land management. As pressure on land resources continues to increase, such scientifically rigorous and practically oriented approaches will be essential for achieving large-scale restoration goals and ensuring the long-term health of our planet's ecosystems.

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