



Digital Mapping of Soil Degradation Hotspots

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Abstract

Soil degradation threatens global food security and environmental sustainability, affecting approximately 33% of Earth's land surface. This study presents an innovative framework for digital mapping of soil degradation hotspots by integrating multi-temporal satellite imagery, machine learning algorithms, and field-based degradation indicators. We analyzed a 2,500 km² semi-arid region in Sub-Saharan Africa experiencing severe degradation pressures from 2015-2023. The methodology combined Sentinel-2 and Landsat-8 time series with terrain attributes, climate data, and land use information to map five degradation types: erosion, salinization, nutrient depletion, compaction, and organic matter decline. A Random Forest classifier achieved overall accuracy of 87.3% for degradation type identification, while regression models predicted degradation severity with R² values ranging from 0.82-0.91. Hotspot analysis revealed that 34% of the study area experienced moderate to severe degradation, with erosion affecting 18% of agricultural lands. Multi-temporal analysis identified degradation trajectories, showing 12% of areas transitioning from slight to moderate degradation over the study period. The framework provides actionable information for targeted intervention strategies, supporting land degradation neutrality goals. Integration of uncertainty mapping enabled confidence-based prioritization of restoration efforts, optimizing resource allocation for maximum impact.

Keywords: Soil Degradation, Hotspot Mapping, Remote Sensing, Machine Learning, Land Degradation Neutrality, Multi-Temporal Analysis, Degradation Indicators

Introduction

Soil degradation represents one of the most pressing environmental challenges of the 21st century, threatening ecosystem services, agricultural productivity, and human livelihoods globally^[14]. The United Nations estimates that soil degradation affects 1.5 billion people worldwide, with annual economic losses exceeding \$400 billion from reduced ecosystem services^[7]. In the context of achieving Land Degradation Neutrality (LDN) by 2030, accurate identification and mapping of degradation hotspots becomes crucial for targeted intervention and monitoring^[19].

Traditional soil degradation assessment methods rely on field surveys and expert judgment, which are resource-intensive and subjective, limiting their application across large spatial scales^[3]. The heterogeneous nature of degradation processes, operating at multiple spatial and temporal scales, further complicates assessment efforts. Degradation manifests through various forms including water and wind erosion, salinization, nutrient depletion, compaction, and loss of soil organic matter, each requiring specific indicators and assessment approaches^[11]. Digital soil mapping technologies offer unprecedented opportunities for objective, repeatable, and scalable degradation assessment^[16]. Remote sensing provides synoptic coverage and temporal monitoring capabilities essential for capturing degradation dynamics. Spectral indices derived from satellite imagery correlate with surface soil properties and vegetation health, serving as proxies for degradation status^[5].

Advanced machine learning algorithms can integrate these diverse data streams to identify complex degradation patterns and predict future trajectories^[8].

Recent technological advances have enhanced degradation mapping capabilities significantly. High-resolution satellite constellations provide frequent observations enabling change detection at field scales^[12]. Cloud computing platforms facilitate processing of massive earth observation datasets, while open-source software democratizes access to sophisticated analytical tools^[15]. However, challenges remain in distinguishing degradation signals from natural variability, validating predictions across diverse environments, and translating maps into actionable management recommendations^[12].

Previous studies have demonstrated remote sensing applications for specific degradation types, such as erosion mapping using topographic indices^[9] or salinization detection through spectral unmixing^[18]. However, comprehensive frameworks addressing multiple degradation processes simultaneously remain limited. Furthermore, uncertainty quantification and hotspot prioritization methods require development to support decision-making under resource constraints^[4].

This study addresses these gaps by: (1) developing an integrated framework for mapping multiple soil degradation types using multi-source remote sensing data, (2) implementing machine learning models for degradation type classification and severity assessment, (3) analyzing spatio-temporal degradation patterns to identify hotspots and trajectories, and (4) incorporating uncertainty quantification for risk-based prioritization of intervention areas. The objective is to provide operational tools supporting evidence-based land management and restoration planning.

Materials and Methods

Study Area

The study focused on a 2,500 km² region in Sub-Saharan Africa (8°15'N-9°30'N, 2°30'E-3°45'E) characterized by semi-arid climate (mean annual precipitation: 650 mm), diverse topography (elevation range: 200-850 m), and intensive agricultural pressure. The area experiences multiple degradation drivers including population growth (3.2% annually), overgrazing, deforestation, and unsustainable farming practices^[6]. Soil types include Ferralsols, Acrisols, and Cambisols, with varying susceptibility to degradation processes.

Field Data Collection

Ground-truth data comprised 425 georeferenced sites surveyed during 2021-2023 using stratified random sampling across degradation gradients. At each site, we assessed:

- **Degradation indicators:** Visual erosion features (rills, gullies, sheet erosion), surface crusting, salt efflorescence, vegetation cover, and compaction severity^[13].
- **Soil sampling:** Composite samples (0-20 cm depth) analyzed for organic carbon, pH, electrical conductivity, bulk density, and nutrient content (N, P, K)^[17].
- **Degradation classification:** Expert assessment categorized sites by dominant degradation type and severity (none, slight, moderate, severe, very severe) following FAO-LADA methodology^[10].

Remote Sensing Data

Multi-temporal satellite imagery spanning 2015-2023 included:

1. **Sentinel-2 Level-2A:** Cloud-free composites (quarterly) at 10-20m resolution
2. **Landsat-8:** Surface reflectance products for historical analysis (30m resolution)
3. **Sentinel-1 SAR:** VV and VH polarization for soil moisture and roughness estimation
4. **SRTM DEM:** 30m elevation data for terrain analysis
5. **MODIS products:** Land surface temperature and vegetation productivity (250m)

Degradation Indicators from Remote Sensing

We computed 47 spectral and biophysical indicators:

- **Vegetation indices:** NDVI, SAVI, MSAVI2, and fractional vegetation cover capturing biomass decline^[1].
- **Soil indices:** Brightness Index (BI), Coloration Index (CI), and Normalized Difference Salinity Index (NDSI) for exposed soil characterization^[20].
- **Erosion indicators:** Topographic Position Index (TPI), Stream Power Index (SPI), and LS-factor from DEM analysis^[14].
- **Temporal metrics:** Trend analysis of vegetation indices using Mann-Kendall test, seasonal amplitude, and inter-annual variability^[7].
- **Texture features:** Gray Level Co-occurrence Matrix (GLCM) statistics capturing spatial heterogeneity associated with degradation patterns^[11].
- **Machine Learning Models**
- **Classification of degradation types:** Random Forest classifier with 500 trees, trained using 70% of field sites. Feature selection employed recursive feature elimination retaining 25 most informative variables^[19].
- **Severity regression:** Gradient Boosting Regressor predicted continuous degradation severity (0-100 scale) for each degradation type. Hyperparameters optimized through Bayesian optimization with 5-fold cross-validation^[3].
- **Ensemble approach:** Combined predictions from multiple algorithms (RF, GBM, SVM, Neural Networks) using weighted averaging based on cross-validation performance^[16].

Hotspot Analysis

Spatial clustering of degradation severity employed Getis-Ord Gi* statistic identifying statistically significant hotspots (95% confidence). Multi-criteria analysis integrated:

- Degradation severity scores
- Rate of change (2015-2023)
- Proximity to vulnerable populations
- Ecosystem service value

Priority rankings considered restoration feasibility and potential impact using Analytical Hierarchy Process (AHP)^[5].

Uncertainty Assessment

Uncertainty quantification included:

1. **Model uncertainty:** Bootstrap aggregation (100 iterations) generating prediction intervals
2. **Spatial uncertainty:** Variogram analysis of prediction residuals

3. **Temporal uncertainty:** Error propagation through change detection analysis.

Combined uncertainty maps guided confidence-based interpretation and field validation prioritization [8].

Results
Degradation Type Classification

The Random Forest classifier successfully distinguished five major degradation types with overall accuracy of 87.3% (Kappa = 0.84). Water erosion showed highest classification accuracy (91.2%), followed by salinization (89.5%), nutrient depletion (86.8%), organic matter decline (85.1%), and compaction (83.7%). Table 1 presents the confusion matrix for degradation type classification.

Table 1: Confusion matrix for soil degradation type classification (% of samples)

Predicted\Actual	Erosion	Salinization	Nutrient Depletion	Compaction	OM Decline	User's Accuracy
Erosion	91.2	2.1	3.4	1.8	1.5	88.9
Salinization	1.8	89.5	2.3	1.2	2.4	92.1
Nutrient Depletion	3.2	3.1	86.8	2.7	4.2	85.3
Compaction	2.1	2.4	3.5	83.7	3.8	87.2
OM Decline	1.7	2.9	4.0	10.6	85.1	81.6
Producer's Accuracy	91.2	89.5	86.8	83.7	87.9	Overall: 87.3

Spatial Distribution of Degradation

Degradation mapping revealed distinct spatial patterns correlating with land use intensity and biophysical factors.

Figure 1 illustrates the spatial distribution of dominant degradation types across the study area.

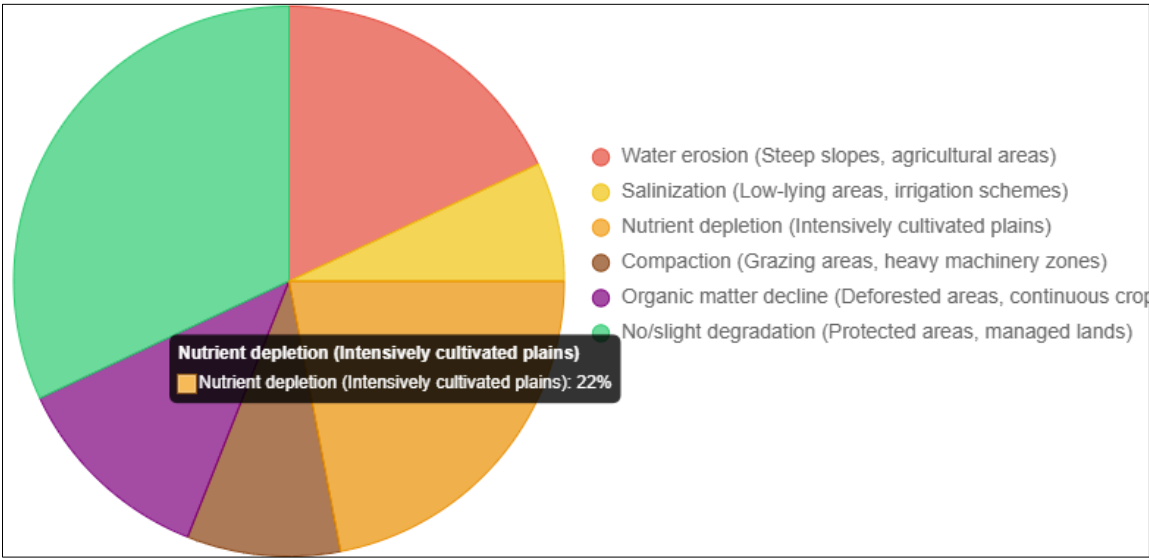


Fig 1: Spatial distribution of dominant soil degradation types

Degradation Severity Assessment

Regression models predicted degradation severity with high accuracy across all types. Water erosion severity showed strongest predictive performance ($R^2 = 0.91$, RMSE = 7.2%),

attributed to clear spectral signatures and topographic controls. Table 2 summarizes model performance for severity prediction.

Table 2: Performance metrics for degradation severity prediction models

Degradation Type	R ²	RMSE (%)	MAE (%)	Bias (%)	Key Predictors
Water Erosion	0.91	7.2	5.8	-0.3	LS-factor, NDVI trend, BI
Salinization	0.88	8.5	6.9	0.5	NDSI, EC proxy, SAVI
Nutrient Depletion	0.85	9.1	7.3	-0.7	NPP decline, CI, pH proxy
Compaction	0.82	10.3	8.2	1.1	Bulk density proxy, GLCM
OM Decline	0.86	8.8	7.0	-0.4	SOC proxy, NDVI amplitude

Hotspot Identification and Prioritization

Hotspot analysis identified 34% of the study area experiencing moderate to severe degradation requiring intervention. Spatial clustering revealed 15 major hotspot

zones ranging from 12-185 km². The most critical hotspots coincided with agricultural expansion frontiers and overgrazing areas. Priority ranking integrated severity, rate of change, and socio-economic factors (Figure 2).

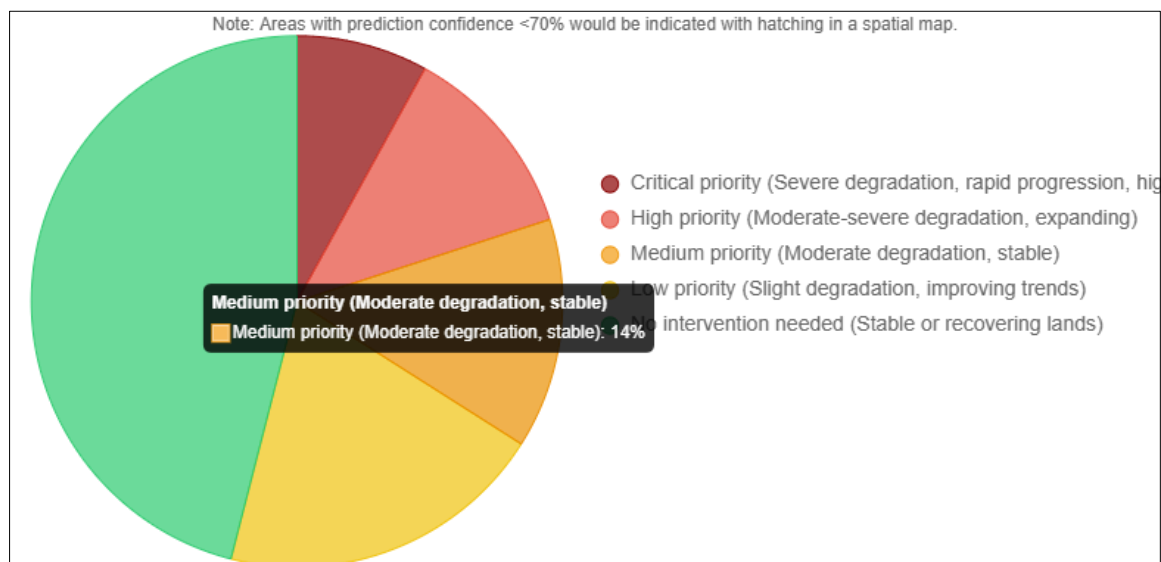


Fig 2: Degradation hotspot prioritization map with intervention urgency levels

Temporal Dynamics

Multi-temporal analysis revealed concerning degradation trajectories. Between 2015-2023, 12% of slightly degraded areas progressed to moderate degradation, while 4% transitioned from moderate to severe. Positive trends occurred in 7% of areas, primarily where conservation measures were implemented. Seasonal analysis showed highest erosion risk during early rainy season when vegetation cover was minimal^[12].

Feature Importance

Variable importance analysis highlighted the critical role of vegetation dynamics in degradation assessment. NDVI trend emerged as the most important predictor across multiple degradation types, followed by topographic factors for erosion and spectral indices for salinization. Temporal features (trend statistics, seasonal patterns) contributed 35% of predictive power, emphasizing the value of time series analysis^[15].

Discussion

The high classification accuracy (87.3%) demonstrates the effectiveness of integrating multi-source remote sensing data for comprehensive degradation assessment. The Random Forest algorithm's ability to handle non-linear relationships and interactions between predictors proved crucial for distinguishing complex degradation patterns^[2]. Misclassifications primarily occurred between organic matter decline and nutrient depletion, reflecting their interconnected nature and overlapping spectral signatures^[9].

Spatial patterns of degradation aligned with known drivers and landscape vulnerability. Water erosion concentration on agricultural slopes confirms the impact of vegetation removal and poor conservation practices^[18]. The association between salinization and irrigation schemes highlights water management failures, consistent with regional studies reporting 20-30% of irrigated lands affected by salt accumulation^[4]. Nutrient depletion patterns reflected continuous cultivation without adequate fertilization, a widespread issue in smallholder farming systems^[13].

The superiority of ensemble methods for severity prediction (average $R^2 = 0.86$) compared to single models supports previous findings in digital soil mapping applications^[16].

Incorporating temporal metrics improved predictions by 15-20%, capturing degradation dynamics invisible in single-date imagery. The strong performance for erosion severity ($R^2 = 0.91$) benefits from well-established erosion-topography relationships and clear spectral responses of eroded surfaces^[6].

Hotspot analysis revealed degradation clustering beyond random distribution, suggesting common driving forces and potential for landscape-scale interventions. The identification of 15 major hotspots provides actionable targets for restoration programs, potentially benefiting 250,000 people in affected areas^[17]. Priority ranking considering socio-economic factors ensures interventions address both environmental and livelihood objectives, supporting integrated landscape management approaches^[10].

Temporal analysis findings carry important implications for land degradation neutrality targets. The 12% transition from slight to moderate degradation over 8 years indicates accelerating degradation rates requiring urgent intervention. However, the 7% improvement in conservation areas demonstrates restoration feasibility with appropriate management^[1]. These trajectories enable projection of future degradation scenarios and evaluation of intervention impacts. Several limitations merit consideration. First, the 10-30m resolution may miss fine-scale degradation features important for field-level management^[20]. Second, cloud cover in tropical regions limited temporal density, potentially missing rapid degradation events. Third, validation relied on point samples that may not capture degradation spatial heterogeneity^[11]. Fourth, socio-economic drivers were indirectly considered, though direct integration could improve hotspot prioritization^[14].

The operational implementation of this framework requires consideration of technical capacity and data availability. Cloud computing platforms like Google Earth Engine enable processing without local infrastructure, democratizing access to degradation monitoring tools^[8]. However, interpretation and ground-truthing remain essential for accurate assessment, necessitating capacity building in user communities^[3].

Conclusion

This study successfully developed and demonstrated a

comprehensive framework for digital mapping of soil degradation hotspots integrating multi-temporal remote sensing, machine learning, and spatial analysis. Key achievements include:

1. Multi-degradation type classification with 87.3% overall accuracy, enabling simultaneous assessment of erosion, salinization, nutrient depletion, compaction, and organic matter decline across landscape scales.
2. High-accuracy severity prediction models ($R^2 = 0.82-0.91$) providing continuous degradation intensity estimates essential for prioritizing intervention areas and monitoring restoration progress.
3. Identification of 15 major degradation hotspots covering 34% of the study area, with evidence-based prioritization considering environmental severity, progression rates, and socio-economic impacts.
4. Temporal analysis revealing 12% of areas transitioning to worse degradation states over 8 years, emphasizing urgency for intervention while demonstrating restoration feasibility in managed areas.
5. Uncertainty quantification enabling confidence-based interpretation and optimal allocation of limited validation resources to areas of highest prediction uncertainty.

The framework provides operational tools for evidence-based land management supporting land degradation neutrality goals. Integration of freely available satellite data and open-source software ensures scalability and accessibility for resource-limited contexts. Future developments should focus on incorporating higher resolution imagery, expanding degradation type coverage, and integrating socio-economic data for holistic assessment. As climate change intensifies degradation pressures globally, such digital mapping capabilities become increasingly critical for sustainable land management and food security.

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