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Review

A bibliometric and systematic review: Linking land use and land cover (LULC) change prediction with soil degradation

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Abstract

Changes in land use and land cover (LULC) are among the main drivers of soil degradation, especially in urban areas under strong development pressure. The lack of land in urban areas often pushes development toward ecologically sensitive areas, such as hillslopes and riverbanks. These practices may alter soil biophysical characteristics and accelerate local-scale environmental degradation. Accordingly, predicting land-use and land-cover change is vital for assessing the potential risk of future soil degradation. Many spatial modeling methods have been developed to predict LULC change dynamics; however, their association with soil quality degradation has yet to be systematically illustrated in the scientific literature. Research on LULC change prediction and its implications for soil quality degradation is widely scattered across the scientific literature. This review conducted a literature search of the Scopus database and analyzed the research trends, methodological approaches, and the relationship between land cover change and soil quality degradation. The review results showed that LULC change is consistently linked to subsequent declines in soil characteristics, such as soil organic carbon, erosion, and soil structural stability. These results underscore the need for predictive models as valuable tools for anticipating soil degradation risks and guiding sustainable land use planning.

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Introduction

Land use change is a worldwide process, driven by global population growth and the demand for space for human activities (Verburg et al., 2008; Verburg, 2014; Wedajo, 2025). According to data from the United Nations Department of Economic and Social Affairs (UN DESA, 2024), over 56% of the global population lives in urban settings today, a trend expected to increase to 68% come 2050 (Shahidehpour et al., 2018; Supangkat, 2018; Saavedra et al., 2024). Residential population growth led to increased demand for land, driving urban sprawl into built-up areas (including industry and infrastructure) (Bîrsănuc et al., 2019; Kamran et al., 2020; Ansar and de Vries, 2024). Land shortage, particularly flat land in urban areas, has driven development into ecologically vulnerable areas such as hillslopes and riverbanks (Ferreira et al., 2018; Nakajima, 2019).

The potential disruption of soil stability and changes in soil biophysical conditions due to slope cutting and land clearing for agriculture/infrastructure development are cataclysmic (da Vitória et al., 2018; Ferreira et al., 2018). These effects alter the land itself, driving poor soil quality and reduced soil organic carbon, with consequences of greater environmental risk, including erosion and landslides (Beroho et al., 2023; Jawarneh et al., 2024). This means that wherever land-use dynamics change, soil quality can be directly reflected in degradation. The prediction of LULC change is an area that has seen, perhaps, the most rapid increase in research activity over the past two decades as LULC models have evolved with advances in remote-sensing technology, spatial analysis, and machine learning-based modelling (Leta et al., 2021; Che et al., 2025; Hussain et al., 2025).

Existing studies have mainly focused on improving the accuracy of land cover change models and on analyzing the determinants of land use dynamics (Li et al., 2017; Ren et al., 2019; Mosleh, 2025). A lot of work has also been done on soil degradation, using various biophysical indicators (e.g., soil erosion, soil organic carbon (SOC) loss, changes in soil physical and/or chemical properties) (Giandon et al., 2010; Rischia et al., 2010; Yameogo et al., 2019). However, these two fields of research have often developed independently in the scientific literature. Soil quality indicators have not been part of the descriptive or predictive analytical framework in most LULC prediction studies, while soil degradation studies are evaluating static land use conditions without projecting future LULC change (Rahmanipour et al., 2014; Samaei et al., 2022; Alebachew and Dengiz, 2025). This scenario reflects a lack of conceptual integration of the dynamics of land-use change and those of soil degradation. This gap points to an important research direction: N or regional soil quality change prediction due to LULC changes should be studied more systematically through systematic literature reviews and bibliometric analyses. This is expected to yield a more complete perspective on trends in research and the potential for integrating land change modelling with soil quality assessment to support sustainable land use planning.

Methods

The objective of this study was to conduct a systematic review of the evolution of research on LULC change prediction and its impact on soil degradation. A systematic literature review (SLR) was applied as the method in this study, guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework and bibliometric analysis (Sitompul et al., 2024; Chan and Nurrosyidah, 2025; Yesuf and Fields, 2025). The PRISMA was applied to the review process: identification, screening, eligibility, and final inclusion (Figure 1).

1. Literature search strategy

The literature search was conducted using the Scopus database as the primary source. The search strategy employed the TITLE-ABS-KEY field with the following keyword combination: ("land use land cover change" OR "land use change" OR "land cover change" OR LULC) AND (prediction OR modelling OR simulation OR "spatial modelling") AND ("soil degradation" OR "soil quality" OR "soil properties" OR "land degradation"). The initial search yielded 927 articles, which were then subjected to the screening stage.

2. Initial literature screening

The screening stage involved reviewing titles and abstracts to ensure the articles were relevant to land cover change prediction and soil degradation. At this stage, the availability of full-text articles was also checked. After the initial screening process, 708 articles were found to meet the preliminary criteria.

3. Eligibility-based selection

Articles that passed the screening stage were then comprehensively reviewed based on the following criteria: discussion of land cover change prediction or modelling, application of spatial modelling approaches, and linkage to aspects of soil quality degradation. Articles that did not meet these criteria were excluded from the analysis. This stage resulted in 42 articles deemed eligible for further analysis.

4. Inclusion stage

Articles that met all eligibility criteria were summarized in Table 1 to present the main characteristics of the analyzed studies before bibliometric analysis. The included articles covered not only direct predictions of LULC change but also studies that modeled soil degradation indicators associated with land use dynamics.

5. Bibliometric analysis

A bibliometric analysis was conducted to map the research landscape related to LULC change prediction and its linkage to soil degradation. This analysis used all articles identified in the initial search as the bibliometric dataset. Article metadata were extracted from the Scopus database, including publication year, authors' country of origin, and research subject categories. Publication trends (Figure 2), geographical distribution of research, and domain scope were described based on these data analysis (Mselle et al., 2021; Singh et al., 2024; Suprayogi, 2024). Furthermore, VOSviewer software was used to conduct bibliometric visualization to examine the relationships among keywords, research topics over time, and emerging thematic clusters in LULC change prediction studies and soil degradation (Abad-Segura et al., 2022; Li and Wei, 2022; Arifin et al., 2023). The types of visualizations used were network, overlay, and density.

Results and Discussion

1. Bibliometric analysis

a. Annual publication trend

The number of publications on the prediction of LULC change during the 2015-2026 period followed a pattern similar to that summarized in the bibliometric trend depicted above (Figure 2).

Table 1. Summary of the analyzed articles.

No	Author(s)	Title	Prediction	Method	Impact on the Phenomena
1	Zhang et al. (2026)	Effect of environmental factors on soil quality across various land-use types in the water-wind erosion crisscross region of China's Loess Plateau	Prediction of Soil Quality Index (SQI) based on soil moisture, organic carbon, water-holding capacity, bulk density, and total phosphorus	PCA, PLS Path Modeling, Obstacle Factor Diagnostic Model, Minimum Data Set (MDS)	Soil quality varies significantly across regions; soil moisture is the primary limiting factor; grasslands exhibit the lowest soil quality in several locations
2	Asmoay et al. (2026)	Integrated assessment of soil and groundwater quality, irrigation suitability, and land-use dynamics in the reclaimed lands of West Mallawi, Egypt	Prediction of Irrigation Water Quality Index (IWQI) using EC, Ca, Mg, Na parameters; prediction of LULC changes 2016–2025	GIS, Remote Sensing, Multiple Linear Regression, PCA, Multivariate Analysis	Soil salinity increased drastically (average EC 8754 µS/cm); soil quality underwent cumulative degradation; agricultural and agroforestry expansion accompanied by urban encroachment
3	Dengiz et al. (2026)	An artificial intelligence approach to the assessment and prediction of soil quality dynamics	Prediction of Soil Quality Index (SQI) from basic soil properties: sand, clay, silt, organic matter, pH, EC, lime, N, P, K	ML-ANN (Artificial Neural Network), Kriging Geostatistik (Simple-Spherical)	SQI ranged from 0.381 to 0.703; ANN prediction correlation r = 0.83 (training); spatial distribution of predicted and actual SQI was similar; additional variables are needed for higher precision
4	Liwur et al. (2026)	After the flames and smoke, then what? Spatial analysis and heterogeneity modeling of bushfire effects on vegetation health and air quality in Ghana	Prediction of bushfire dynamics, vegetation health (NDVI, NBR), and air quality (PM2.5, CO, SO_2) spatiotemporally	MGWR (Multiscale Geographic Weighted Regression), LULC Classification, NDVI, NBR, GIS	More than 60% of the landscape was affected by fire; NDVI declined >70%; PM2.5 increased from 28 to 35 µg/m³, ecological degradation and public health impacts intensified
5	Thakur et al. (2026)	Integrating CA–Markov–ANN for spatiotemporal prediction of land use dynamics in a fragile Himalayan watershed	Prediction of LULC changes for 2035 and 2045: glacier/snow cover, built-up areas, Himalayan moist temperate forests	CA-Markov Chain-ANN (CA-MC-ANN), MLP (Multi-Layer Perceptron), GIS, Remote Sensing	Glacier/snow cover declined from 37.66% (1989) to 13.47% (projected 2045); built-up areas increased; severe pressure on Himalayan-mountain ecosystems
6	Teku et al. (2026)	Optimizing flood hazard zonation and planning landscape-based mitigation measures in Gimba Sub Watersheds, Northeastern Ethiopia	Prediction of flood hazard zones based on drainage density, rainfall, slope, elevation, LULC, soil type, geology, and groundwater depth	AHP (Analytical Hierarchy Process), GIS Spatial Modeling, ROC-AUC Analysis	34.6% of the watershed falls within high/very high flood hazard zones; AUC = 0.885; 32.1% of the area is suitable for nature-based solutions (agroforestry, terracing, reforestation)

No	Author(s)	Title	Prediction	Method	Impact on the Phenomena
7	Al-Hashim et al. (2026)	Assessing potentially toxic element contamination in agricultural soils of an arid region: a multivariate and geospatial approach	Prediction of spatial distribution of toxic element contamination (Ni, Mn, Pb, Cr, Zn, As) in arid agricultural soils	GIS, Remote Sensing (LULC), PCA, Contamination Indices (EF, CF, Igeo, PLI, RI)	Ni and Mn exceeded international threshold levels; PLI 0.24–0.80 (low-moderate contamination); RI 10.43–41.38 (low ecological risk); contamination hotspots were identified
8	Boroughani et al. (2026)	Linking dust source susceptibility mapping and land use change in Middle East	Prediction of LULC changes and dust storm susceptibility for years 2040, 2070, and 2100	CA-Markov Model, ML (Boosted Regression Trees/BA, XGBoost, CA), GIS	Barren land and zero-vegetation areas increased significantly; urban sprawl aggravated degradation of agricultural land; Middle East regions are highly susceptible to dust storms
9	Nardotto Júnior et al. (2026)	Land conservation based on land use potential and erosion risk in an Atlantic Forest watershed (Brazil)	Prediction of soil erosion potential and land use suitability in the São Mateus River Basin	CUP (Conservation Use Potential), RUSLE (Revised Universal Soil Loss Equation), GIS	38.91% of the area has high agricultural potential; 9.39% of land use is incompatible; 3.18% of the area exceeds erosion tolerance for tropical soils
10	Szatmári et al. (2026)	HU-SoilCarbonGrids: An initiative for providing comprehensive information on soil organic carbon changes in Hungary	Prediction of annual Soil Organic Carbon (SOC) stocks at 100 m resolution from 1992-2023 across Hungary	ML (Machine Learning), Digital Soil Mapping, Kriging, Space-Time Modelling	Net declining trend in SOC over 32 years; forests increased, wetlands declined, croplands and grasslands fluctuated; important database for soil health monitoring
11	Thakur et al. (2025)	Evaluation of land degradation vulnerability in coal mined areas of Madhya Pradesh, India	Prediction of Land Degradation Vulnerability Index (LDVI) and land use change patterns in coal mining areas over 40 years	GIS, AHP (Analytical Hierarchy Process), Maximum Likelihood Algorithm, Satellite Data Analysis	51.07 km^2 of forest and 33.39 km^2 of agricultural land lost between 1984-2024; LDVI increased drastically; 47.32% of the landscape is vulnerable to degradation
12	Senthilkumar et al. (2025)	Coastal spatial planning using object-based image analysis and image classification techniques	Prediction of coastal LULC changes in Rio de Janeiro for years 2035 and 2045	OBIA (Object-Based Image Analysis), QGIS Molusce Tool, ML Image Classification	Built-up areas increased from 29.33% to 43.99%; agricultural land declined from 21.32% to 5.59%; forest cover decreased; urbanization pressure and environmental degradation intensified
13	Amin et al. (2025)	Assessment and monitoring of land degradation indicators and processes using a geospatial approach	Prediction of spatial distribution of land degradation indicators: water erosion, waterlogging, vegetation	GIS, Remote Sensing Multi-Temporal (2001-2019), Supervised	More than 25% of the area experienced land degradation; water erosion on unirrigated land was the most dominant; mapping accuracy was 86%

No	Author(s)	Title	Prediction	Method	Impact on the Phenomena
			degradation, anthropogenic impacts	Classification, LULC Analysis	
14	Khan et al. (2025)	Long-term effects of crop treatments and fertilization on soil stability and nutrient dynamics in the Loess Plateau	Prediction of soil quality, aggregate stability, and soil fertility based on fertilization type and long-term land use	PLS-M (Partial Least Squares Modeling), Mantel Analysis, Analisis Fisiko-Kimia Tanah	Combined organic-inorganic fertilization (NPM) was most effective; alfalfa fields with NPM showed the highest fertility; the 0–10 cm layer was most responsive to treatments
15	Richiedei et al. (2025)	Sub-regional biophysical and monetary evaluation of ecosystem services: an experimental spatial planning implementation	Prediction of biophysical and monetary values of 6 ecosystem services based on soil quality over two time periods	GIS Spatial Modeling, InVEST Model, Biophysical & Monetary Quantification	Land cover transformation led to a decline in ecosystem services; the methodology is applicable to sub-regional spatial planning; supports soil protection policies
16	Sabitha et al. (2025)	Estimation of potential impact of land use change on sediment yield from a small tropical watershed using the TREX erosion model	Prediction of short-term (2025, 2029) and long-term (2037–2053) sediment yield and runoff under LULC change scenarios	TREX Erosion Model, CA-ANN (Cellular Automata-Artificial Neural Network)	Peak runoff increased 29%, runoff volume 22%, sediment yield 50%, peak sediment concentration 56% from 2005–2053; urbanization was the primary driver
17	Irawan and Setiawan (2025)	Forecasting the long-term impacts of land use and cover changes on runoff coefficient and flood hydrograph: Upper Citanduy Basin, Indonesia	Prediction of runoff coefficient and flood hydrograph due to LULC changes through 2029	CA-ANN (MOLUSCE/QGIS), HEC-HMS (SUH: Nakayasu, Snyder, Clark)	Composite runoff coefficient increased by 16.97% (2014-2029); 5-year return period peak discharge in 2029 approached the 25-year return period in 2019; conversion of agricultural land to built-up areas was the main driver
18	Li et al. (2025)	Land use patterns change N and P cycling bacterial diversity in an acidic karst soil	Prediction of changes in N and P cycling bacterial communities in karst soil based on land use patterns	PLS Path Modelling, Shotgun Metagenomics, Analisis Fisiko-Kimia Tanah	All land management practices reduced bacterial diversity; N and P cycling in karst soil was disrupted; functional diversity declined due to land use intensification
19	Liu et al. (2025)	Quantifying uncertainty in projections of desertification in Central Asia using Bayesian networks	Prediction of desertification risk 2030–2050 based on vegetation quality, precipitation, land use intensity, and soil quality under SSP245 and SSP585 scenarios	Bayesian Networks, ESAS Model, GIS (Google Earth Engine), Climate Downscaling	Desertification risk increased by 4% (SSP245) and 11% (SSP585) by 2050; Kazakhstan, Uzbekistan, and Turkmenistan are the most threatened; vegetation quality is the dominant factor

No	Author(s)	Title	Prediction	Method	Impact on the Phenomena
20	Juknelienė et al. (2025)	Driving forces of agricultural land abandonment: A Lithuanian case	Prediction of agricultural land abandonment patterns using Markov Chain based on geographic and socio-economic factors	Markov Chain Model, GIS, Qualitative Expert Survey, Orthophoto Analysis	Natural factors (proximity to forests, topography) and socio-economic factors (land ownership, migration) determine land abandonment; soil quality impact varies depending on local data accuracy
21	Mungai et al. (2025)	Spatial-temporal modeling of land-use dynamics at the agricultural-forest interface: insights from Ntchisi District, Malawi	Prediction of land cover for 2030 based on land use transitions from forest and shrubland to cropland and built-up areas	ML Random Forest, MLP (Multi-Layer Perceptron), Markov Chain, GIS, Landsat/Sentinel-2	Cropland and built-up areas increased during 2019-2022; tree cover is projected to continue declining by 2030; supports identification of degradation and restoration hotspots
22	Abbood et al. (2025)	Regional change prediction of land degradation risks using Cellular Automata-Markov modeling in Dhi Qar Province, Iraq	Prediction of land cover change and land degradation risks for years 2034 and 2044	CA-Markov Model, GIS, Supervised Classification (Landsat 5/7/8/9)	Sand dune areas increased from 8,128 ha to 18,240 ha; desertification and vegetation decline continued; agricultural land remained relatively stable over the 20-year projection
23	Rivera-Fernandez et al. (2025)	Spatiotemporal land cover change and future hydrological impacts under climate scenarios in the Amazonian Andes	Prediction of LULC changes and hydrological impacts (water flow, percolation, lateral flow) under climate scenarios SSP2-4.5 and SSP5-8.5	SWAT Model, Multi-Temporal LULC Analysis, GIS, Climate Scenario Modeling	Minimum monthly streamflow decreased by up to 73.9%; peak flow increased by 14.8%; water storage capacity declined; land degradation and water insecurity intensified
24	Yan et al. (2025)	Analysis and prediction of spatial and temporal variation of carbon storage in limestone area (Hongshui River Basin)	Prediction of ecosystem carbon storage in 2030 under three scenarios: natural development, urban development, and ecological protection	InVEST Model, PLUS Model, Geographic Detector, GIS	Carbon storage increased by 71.59×10^6 t during 1990-2020; the ecological protection scenario yielded the highest carbon storage by 2030; land use was the main driving factor (q = 0.833)
25	N'Danikou et al. (2025)	Change monitoring and assessment of land use and land cover for the municipality of Ouessè in Benin	Prediction of LULC changes (woodland, agricultural land, plantations, rock domes) through 2049	CA-ANN (MOLUSCE/QGIS), GIS, Landsat Classification	Significant changes in woodland and agricultural land from 1986–2019; further shifts projected through 2049; smart agricultural technologies and sustainable business models are needed
26	Weng et al. (2025)	Unveiling divergent trends in soil erosion and soil organic carbon displacement in	Prediction of soil erosion rates and SOC displacement for 2031–2050 under CMIP5	CMIP5/CMIP6 Climate Models, RUSLE, SOC	CMIP5 projects increased erosion; CMIP6 projects an average erosion reduction of 39 t/km²/year; land use change contributed 254% to erosion

No	Author(s)	Title	Prediction	Method	Impact on the Phenomena
		response to climate and land-use changes over China	(RCP8.5) and CMIP6 (SSP5-8.5) scenarios	Displacement Modeling, GIS	under CMIP6; implications for soil conservation policy
27	Kah et al. (2025)	Hydroclimatic trends and land use changes in the continental part of the Gambia River Basin	Prediction of hydroclimatic trends (SPEI) and LULC changes and their implications for water resources	GIS, Remote Sensing, SPEI Analysis, Trend Analysis (Mann-Kendall), LULC Classification	Forest cover decreased by 20.57% (1988-2002) but recovered after 2008; agricultural land and bare soil increased by 14%; land degradation was exacerbated by human activities and climate variability
28	Wei and Jiang (2025)	Multi-scenario simulation analysis of land use change in Hangzhou using the SD-PLUS model	Prediction of land use change in Hangzhou for 2030 under SSP1-2.6, SSP2-4.5, and SSP5-8.5 scenarios	SD-PLUS Coupled Model (System Dynamics + PLUS), GIS, Climate Scenario (SSP-RCP)	Construction land increased by 608.94 km^2 under SSP5-8.5; ecological land declined under SSP2-4.5 and SSP5-8.5; SSP1-2.6 was most effective in protecting ecological land
29	Putra et al. (2025)	Potential erosion and sedimentation based on land use change by using cellular automata-artificial neural network	Prediction of erosion and sedimentation based on a business-as-usual LULC scenario for 2025	CA-ANN, USLE Model, InVEST Model (Sediment Retention), GIS, Remote Sensing (Sentinel-2A)	Deforestation exceeded 35% of the total area by 2025; erosion increased by 25% and sedimentation by 18% (2022), projected to increase further; global fertile soil loss reaches 75 billion tons per year
30	Dutta et al. (2025)	Identification of soil erosion-susceptible areas using fuzzy logic and hydrological indices aided by mineralogical-granulometric analysis	Prediction of soil erosion-susceptible zones based on rainfall, aspect, topography, LULC, NDVI, slope, and soil mineral composition	Fuzzy Logic Modeling, Hydrological Indices Analysis, GIS, XRD (X-Ray Diffraction), Grain Size Analysis	80% of soils are sandy; northern and northwestern regions are most erosion-prone; 37% of the area has severe erosion potential; vulnerability maps support sustainable land conservation planning
31	Riyanto et al. (2025)	The decline in water level and discharge of Lake Toba of North Sumatera, Indonesia, affected by land degradation	Prediction of water balance and inflow to Lake Toba under vegetative and civil engineering conservation scenarios	SWAT (Soil and Water Assessment Tool), GIS, LULC Analysis	Dry fields increased from 72,961 ha to 125,000 ha; lake water level dropped from 905 to 903 m asl; discharge declined from 180 to 125 m^3/s; vegetative conservation could potentially increase inflow to 250 m^3/s
32	Desalegn et al. (2025)	Impact of land use/land cover changes on soil erosion risk in upper Mile River sub-	Prediction of soil erosion risk and annual soil loss rate based	RUSLE (Revised Universal Soil Loss Equation), GIS	Soil loss rate increased from 16.07 to 17.26 t/ha/year (2003) then declined to 12.94 (2018) following area closure

No	Author(s)	Title	Prediction	Method	Impact on the Phenomena
		watershed, North Eastern highlands of Ethiopia	on LULC changes from 1989–2018		interventions; 58.9% of the area has low erosion risk
33	Lari et al. (2025)	Quantifying sediment yield and discharge fluctuations using the GeoWEPP in response to soil and water conservation practices	Prediction of sediment yield and discharge fluctuations based on 8 biological conservation scenarios with varying canopy cover density	GeoWEPP Model, GIS, LULC Analysis, Snowmelt Runoff Modeling	Increasing canopy cover reduced runoff and sediment by up to 44% and 47%; the channel-cover scenario increased runoff 54% and sediment 67%; NSE = 0.74, R^2 = 0.84
34	Hasanuzzaman et al. (2025)	Integrated DSAS and CA-Markov model approach for assessing gully erosion dynamics and land use transformations	Prediction of gully erosion rates and LULC transformations for 2032 in two contrasting watersheds in India	DSAS (Digital Shoreline Analysis System), CA-Markov Model, GIS, ROC Analysis	Gully erosion in SNSW was three times faster than in RSW; vegetation-to-cropland conversion reached 33.8% in SNSW; deforestation → gully expansion → agricultural encroachment identified as the degradation cycle
35	Aregaw et al. (2025)	Comprehensive land degradation assessment using geospatial modeling approach, the case of Dega Damot District, Northwestern Ethiopia	Prediction of a composite land degradation map from soil erosion, vegetation degradation, and biodiversity degradation	GIS, RUSLE, AHP, ML Supervised Classification (Maximum Likelihood), Remote Sensing (Landsat)	75% of the area had the highest soil erosion severity; high and very high land degradation covered 36% of the area; biodiversity hotspot maps are useful for sustainable resource management
36	Hassan et al. (2025)	Modelling the spatial distribution of drought effects on land degradation in the Blue Nile Region, Sudan	Prediction of spatial distribution of drought-induced land degradation using vegetation indices (NDVI, SARVI, SAVI, VHI) and soil indices (BSI, TGSI)	GIS, Kriging Model, Vegetation & Soil Indices (NDVI, SARVI, SAVI, VHI, BSI, TGSI), PCA	Very severe and severe degradation increased by 15.8% and 23.3%; Kriging model R^2=0.52, Kappa=72%; cost-effective method for monitoring degradation in semi-arid regions
37	Ramachandra et al. (2025)	Sustainable management of natural resources at disaggregated levels with insights from landscape dynamics	Prediction of land use dynamics and Natural Resource Rich Region (NRRR) status using multi-temporal satellite image classification	ML Random Forest (RF), GIS, Remote Sensing, Fragmentation Metrics	Built-up areas increased from 186.22 km^2 (1973) to 1085.12 km^2 (2022); intact forest declined from 3252.39 to 1508.12 km^2; NRRR1 and NRRR2 zones were prioritized for conservation
38	Tamiru et al. (2025)	Effect of structural variation in selected woody species on selected soil chemical	Prediction of soil chemical properties (total N, available P, available K, EC) based on LULC changes and vegetation	ML Random Forest (RF), GIS, Lab Soil Analysis, LULC Change Detection	Agroforestry increased by 41.2%; forest cover declined by 47.2%; N was higher on upper slopes; forest had

No	Author(s)	Title	Prediction	Method	Impact on the Phenomena
		properties in the mountain of Hangadi Watershed, Ethiopia	structure (agroforestry vs. forest)		higher AvK and EC; agroforestry had higher available P
39	Alikhanova et al. (2025)	Tracking vegetation dynamics in drylands with MSAVI: Insights from the South Aral Sea	Prediction of Aboveground Biomass (AGB) and vegetation productivity trends in afforested areas during 2013–2023	MSAVI (Modified Soil Adjusted Vegetation Index), GAM (Generalized Additive Model), GIS, Remote Sensing	Strong correlation between MSAVI and AGB ($\rho = 0.8238$); overall land productivity was stable; degradation hotspots were found in former wetland areas; MSAVI is effective for monitoring dryland afforestation
40	Cherigui et al. (2025)	Urban expansion and its environmental impacts in northwestern Algeria using cellular automata-Markov-chain modeling	Prediction of LULC changes (built-up areas, forest, agricultural land, shrubland, grassland, barren land) through 2051	CA-MC (Cellular Automata-Markov Chain), ANN (Artificial Neural Network), GIS, Landsat	Built-up areas increased by 617% (2001–2021); forest cover declined by 8% and agricultural land by 40%; 2051 projections: built-up areas +23.3%, forest -14.27%; ecological balance is at risk
41	Erfanian et al. (2025)	Employing habitat suitability modeling to assess the distribution and envenomation potential of scorpion species in Iran	Prediction of spatial distribution of scorpion habitat suitability based on bioclimatic variables and soil temperature layers	Habitat Suitability Modeling (Ensemble of 9 algorithms), GIS, Bioclimatic Variables, Soil Temperature Layers	Scorpion diversity hotspots are located in southern and southwestern Iran; hotspots are unprotected and threatened by land use change; human–scorpion conflict risk is highest in hotspot areas
42	Doubleday et al. 2025)	Impacts of year-to-year weather variability and inter-panel spacing on agrivoltaic crop yields in Massachusetts	Prediction of crop yields (broccoli, peppers, kale, Swiss chard) in an agrivoltaic system based on inter-panel spacing and annual weather variability	Field Experiment, Agrivoltaic System Analysis, Statistical Analysis	Kale showed a positive trend with increasing panel spacing; agrivoltaic yields were equivalent to full-sun fields in hot, dry years; significant year-to-year variability observed; soil quality and water use efficiency improved

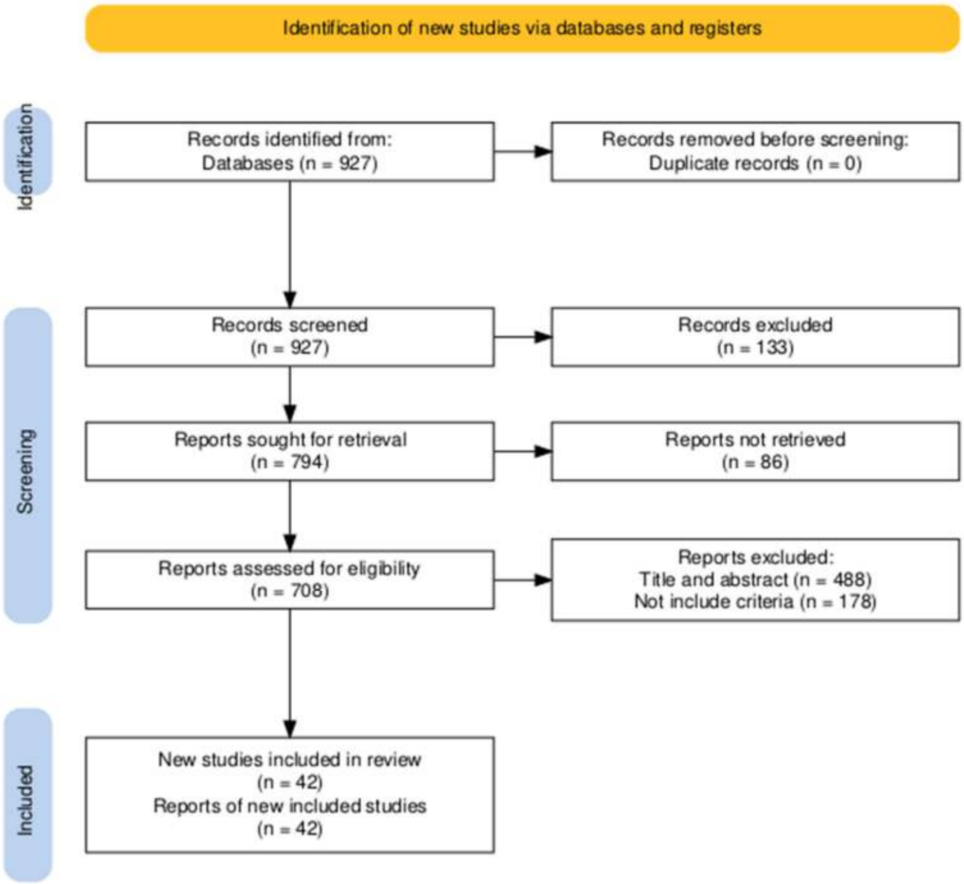

Figure 1. PRISMA flowchart of the selection of articles.

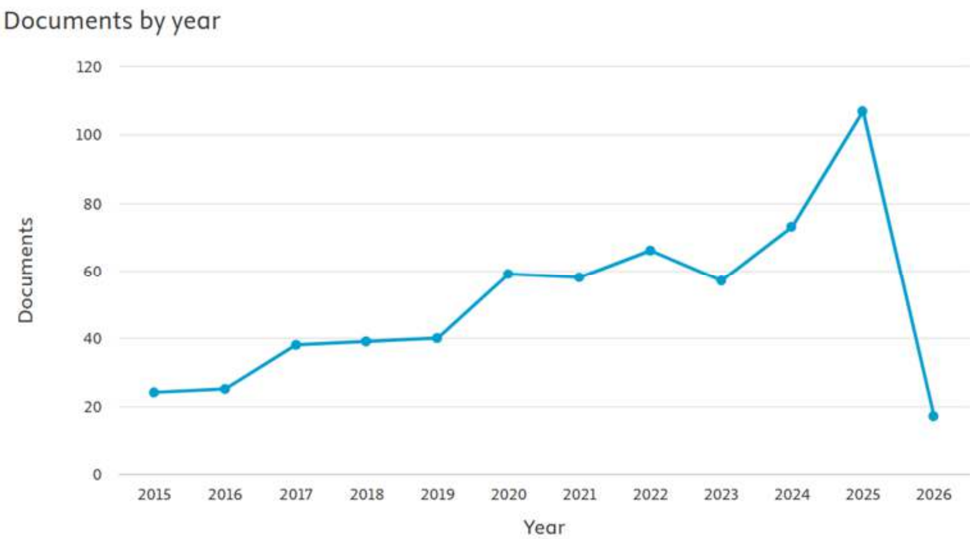

Figure 2. Publication trend in LULC prediction research during 2015-2026.

Overall, from 2015 onward, the number of publications exhibited a slow upward trend, indicating increasing research interest in dynamic LULC changes and their effects on soil quality (Arsyad et al., 2024; Ahmad et al., 2025; Nahid et al., 2025). A slight increase is seen in the early period (2015-2017), from around 24 to just under 38 documents. After 2020, publication output remained at a high level, with normal fluctuations, rising in 2022 and 2024, indicating sustained interest from the scientific community in LULC change prediction. The publication peak was recorded in 2025, exceeding 100 documents, suggesting that this issue has become an increasingly major focus in environmental research, spatial modelling, and regional planning. The decline in publications in 2026 is likely attributable to incomplete publication data for the current year (the incomplete-year effect). It, therefore, should not be interpreted as a substantial decline in research interest.

b. Distribution across research fields

The distribution of publications by subject area shown in the figure above indicates that research on LULC change prediction is highly multi-disciplinary in nature (Choudhary et al., 2018; Muhammad et al., 2022; Hu et al., 2026). Environmental Science is the most dominant category, accounting for approximately 34.6%, indicating that LULC studies generally focus on environmental issues, land change dynamics, soil degradation, and their impacts on ecosystems. They are Agricultural and Biological Sciences (20.5%), which is the second-ranked field, suggesting a focus on the relationship between LULC change and agricultural productivity, plant ecology, and ecosystem functioning. Earth and Planetary Sciences accounts for approximately 16.9%, reflecting extensive consideration of physical geography, land-surface change, geomorphology, and spatial processes related to land-use dynamics. In addition, Social Sciences contributes significantly (9.3%), indicating that studies related to LULC not only explore biophysical dimensions but also address socio-economic impacts related to urbanization, spatial planning policies, population growth, and settlement patterns.

This finding highlights that land use change is a phenomenon shaped by interactions between human activities and the environment. Contributions from Decision Sciences (3.0%), Computer Science (2.3%), Biochemistry, Genetics and Molecular Biology (2.0%), and Engineering (1.8%) further demonstrate support from technical and computational disciplines. Studies in these fields are generally associated with the development of spatial modelling methods, machine learning algorithms, GIS, and remote sensing applications, as well as quantitative and predictive analyses that provide an essential foundation for LULC change simulation. Other categories, such as Energy, Multi-disciplinary, and Other, although representing smaller proportions, indicate that this topic also intersects with additional scientific domains, further confirming its cross-disciplinary nature.

c. Geographic distribution of publications

Figure 3, showing the distribution of publications by country, indicates that research on LULC change prediction has a global distribution, with strong dominance by countries possessing high research capacity (Leta et al., 2021; Afuye et al., 2024; Akhila and Pramada, 2025). China is the most significant contributor, with over 160 publications, far ahead of any other country.

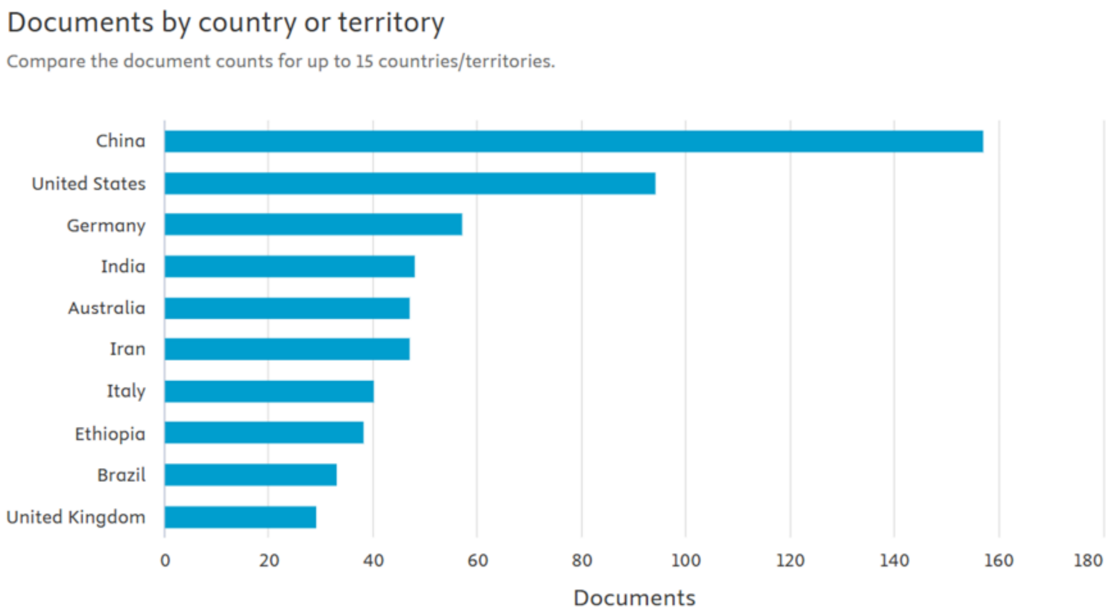

Figure 3. Geographic distribution of publications by country.

The three countries are likely the major global hubs of LULC-related research. Other countries, such as those with emerging research on land change and soil degradation in South Asia (e.g., India), Oceania (Australia), and the Middle East (Iran), contribute around 40–50 publications each. Other countries, such as Italy, Ethiopia, Brazil, and the United Kingdom, also contribute, but with a lower publication output than the leading countries. The dominance of Asian countries, particularly China and India, indicates strong pressures from urbanization, industrialization, and land use conversion, thereby encouraging the development of predictive studies in these regions. Contributions from European countries and the United

States further indicate that regions with strong research traditions continue to advance new approaches in LULC modelling.

d. Keyword-based analysis using VOSviewer: network visualization, overlay visualization, and density visualization

1. Network visualization

The bibliometric analysis of the keyword network shows that research on land use change, erosion processes, and soil quality is organized into three major thematic clusters that are interconnected but have developed along relatively independent research trajectories (Cheng et al., 2021; Delcourt et al., 2023; Sun et al., 2025).

The first cluster centers on LULC dynamics and land degradation, as reflected by the dominance of terms such as land use change, land degradation, land cover, deforestation, and urbanization. The presence of supporting concepts such as remote sensing, GIS, and various forms of modelling indicates that spatial data-based analysis has become the primary approach for understanding landscape transformation.

The second cluster focuses on erosion processes and hydrological mechanisms, characterized by terms such as soil erosion, soil loss, sediment transport, runoff, and watershed. Research within this cluster generally evaluates the relationships among rainfall, surface runoff, and the capacity of land systems to retain or mobilize sediments.

The third cluster is related to soil quality and soil health, as indicated by terms such as soil quality, soil organic matter, soil organic carbon, soil moisture, and biogeochemical components that reflect the ecological functions of soil in supporting productivity and environmental sustainability.

Together, these three clusters show that each domain has developed intensively. However, conceptual integration linking land change dynamics, erosion processes, and soil quality indicators remains limited.

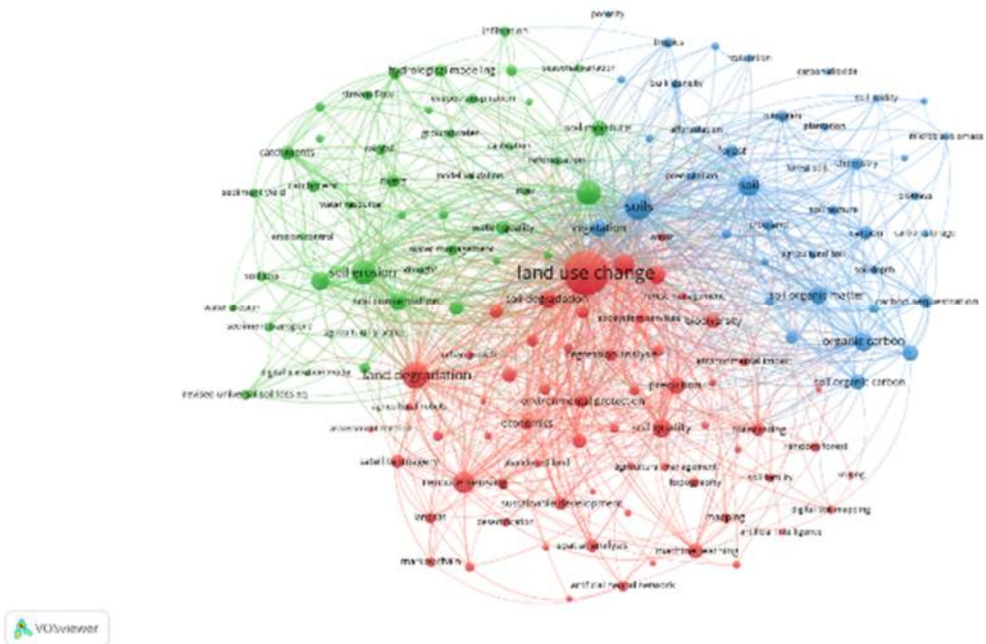

Figure 4. Keyword network visualization from VOSviewer.

The development of the literature over the past two decades reveals a similar pattern. Studies on land cover change have increased rapidly to address the need to understand built-up area expansion, deforestation, and changes in land function. At the same time, research on soil quality has advanced to evaluate the physical, chemical, and biological properties of soil that underpin ecosystem sustainability. Meanwhile, studies on soil erosion and hydrological processes have continued to deepen through the development of models to predict soil loss, surface runoff, and sediment dynamics. As such, despite substantial growth in research on these three fields, direct interconnections among them are rarely developed within a single comprehensive analytical framework. The network visualization based on keywords consistently points to this structural separation by revealing the three main research clusters that represent its actual thematic pillars. The land change cluster is a prime example of spatial factors and land use changes playing critical roles in environmental processes. An example of various soil health indicators, such as organic carbon content, moisture, and biogeochemical properties, in the context of the soil quality cluster. On the other hand, the erosion and hydrology cluster depicts the interaction among rainfall, surface runoff, and sediment mobilization processes. The network provides a first indication of interconnections between the clusters; however, a higher degree of integration seems to be needed to bring all elements together within a single holistic ecological framework. The conceptual space between these three themes represents a significant opportunity for further research. For example, processes of land change dynamics, soil quality degradation, and erosion are interrelated phenomena that cannot be comprehended independently. Developing research approaches that can address these three components in parallel would yield a deeper understanding of mechanisms of environmental change. By doing so, these integrative efforts would not only enhance the scientific rigor of land degradation research but also provide a more robust foundation for addressing issues such as land use planning, soil conservation, and sustainable environmental management across various geographical contexts.

2. Overlay visualization

Early Phase-Earlier Topics (Blue)

The blue cluster (Figure 5), characterizing early research development around 2018 to 2019 in the first stage of research advancement, exhibited dominant topics, with a significant emphasis on hydrological issues (notably upstream–downstream water distribution/contribution) and biophysical land features. The occurrence of keywords such as SWAT, sediment, watershed, catchment, hydraulic conductivity, soil profile, and soil texture suggests that the majority of studies from this period focused on river flow dynamics and sedimentation processes in concert with the physical condition of soils within systems. Classical hydrological approaches (erosion modelling, watershed characterization, estimation of the soil physical parameters) were still prevailing in research orientation as major components for understanding land vulnerability.

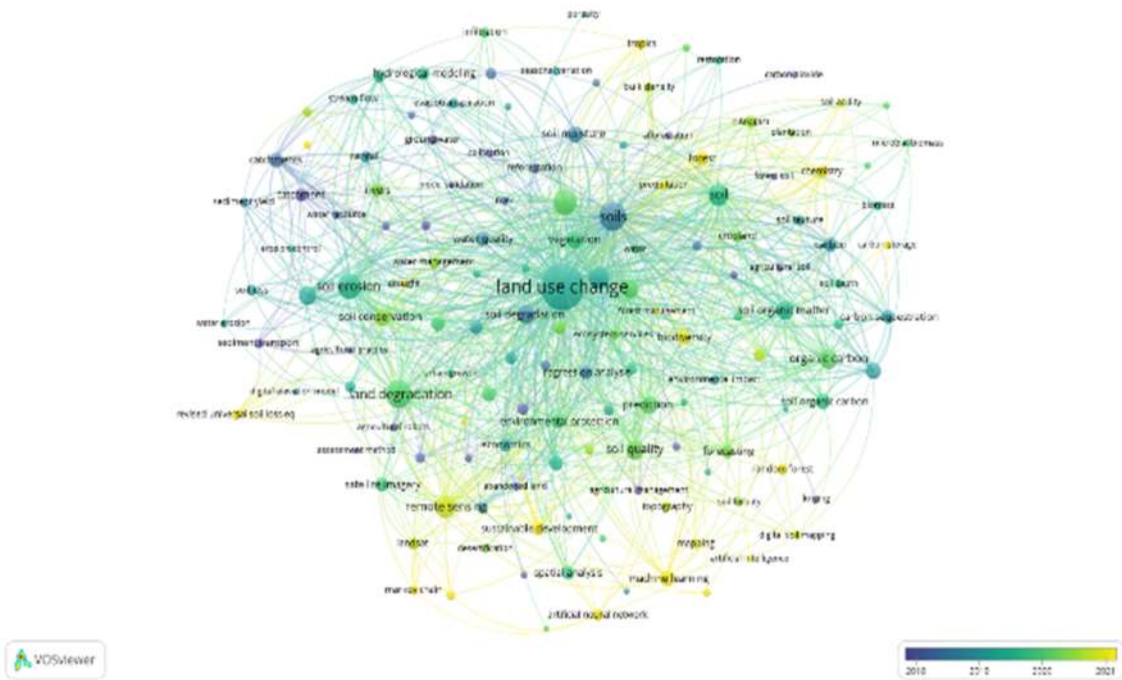

Figure 5. Overlay visualization of keyword temporal development.

Transitional Phase-Emerging Topics (Green)

During 2020-2021, the keyword network had transitioned toward green clusters (Figure 5), with a more integrated aspect, Including Soil organic carbon, bulk density, land degradation and expansion, as well as LULC among the most abundant keywords identified during this phase. The dominance of these terms indicates that research began to combine land-use change dynamics with the biophysical characteristics of soils and various land-degradation processes. Whereas earlier studies tended to be partial, separating soil analysis from land change, this stage marks a transition toward a more comprehensive approach.

Recent Period-Current Issues (Yellow)

Additionally, predictive models based on machine learning and remote sensing are applicable only after the epidemiological data have been acquired (e.g., during the yellow phase, Figure 5). However, this is more apparent in the keyword network used in recent years, especially around 2022, when many yellow nodes capture the latest trend in research development. This review also found that the most relevant keywords gradually shifted from terms such as LULC, Universal Soil Loss Equation (USLE), machine learning, accuracy, classification, GIS, remote sensing, and Landsat to more modern analytical approaches. By then, more studies used machine learning algorithms to predict land use change and estimate soil loss, along with increased effort in model validation and predictive accuracy. The increasing popularity of medium-resolution satellite imagery, such as Landsat, and the development of big data-based spatial analytics, deep learning (DL), and the tight integration between remote sensing and GIS are also being witnessed. These recent trends indicate that research has shifted from traditional paradigms towards data-driven predictive frameworks, where increasingly adaptive, automated, and accurate modelling has become key to understanding land change dynamics and environmental degradation.

No doubt, the trend overgrown with more recent studies is gradually integrating LULC change with soil biophysical properties through integrated studies focusing on surface hydrology, erosion and soil physical characteristics (blue phase), but also including aspects of land use change and low impact development systems to conserving soils from degradation (green phase) highlights a clear dominance on those approaches, thus the integration of simulated predictions for LULC changes being linked up to assess widely applicable indicators for soil quality degradation until now has been quiet limited as also looming after current developments in research spotlight.

3. Interpretation of Density Visualization

The keyword density visualization (Figure 6) shows bright yellow nodes indicating the densest areas, which are clustered around terms such as land use change, soil, soil organic carbon, land degradation, soil degradation, vegetation, LULC, expansion, and carbon. The strong concentration indicates that investigations into soil properties and quality, land degradation, land-use change dynamics, and soil carbon-related processes are the central topics of the current research landscape. That is, aspects of soil quality and land-use conversion seem to be the main focus of this body of research, and dynamics involving soil organic carbon serve as a significant connecting factor.

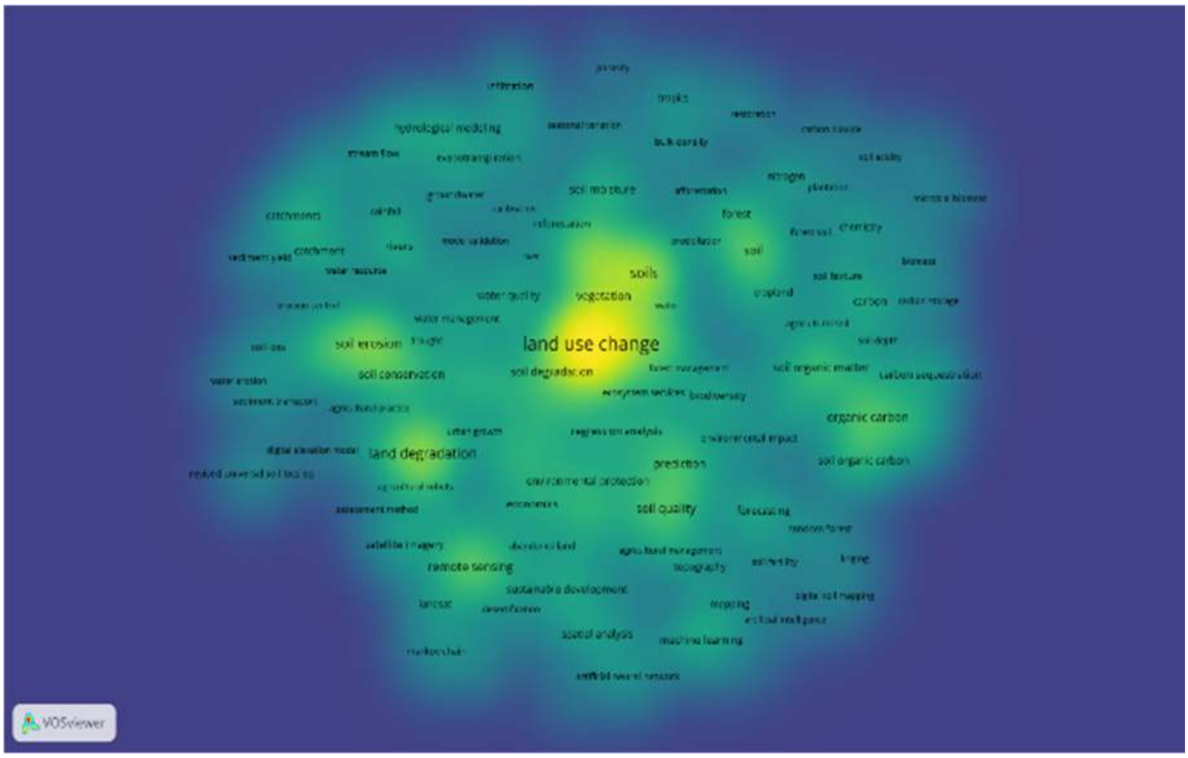

Figure 6. Keyword density visualization.

Away from this hub, moderate-density nodes include terms associated with machine learning and statistical analysis, such as discrimination and accuracy, as well as remote sensing, digital elevation models (DEMs), and sediment yield, which show that technical means of digital soil mapping are emerging but remain ancillary tools. Indeed, these modern approaches, spatial analytics, machine intelligence, and soil loss modelling, are increasingly applied, but not as the fundamental or key focal point of the research network. In addition, the relatively small number of studies that directly relate the outputs of LULC change predictions to indicators of soil quality degradation indicates that attempts to assess impacts on soil quality based on future projections are still in an early stage. This condition indicates that although themes related to soil characteristics, land degradation, and land use dynamics dominate current research, predictive approaches and data-driven methodologies have not yet been fully integrated into soil-quality analysis. Given their lower density, terms related to machine learning and spatial modelling suggest that these methodological innovations are still evolving and have not yet become the main focus of the literature. Therefore, there is substantial research potential to develop approaches that systematically link LULC change prediction with indicators of soil quality degradation, thereby supporting decision-making for sustainable land-use planning.

2. Synthesis of Included Articles

The synthesis of the 42 selected articles shows that research on LULC change prediction and its implications for soil degradation has progressed rapidly during recent decades. Every paper in the dataset shares a similar signature of satellite image-based modelling, machine learning, spatial analysis, and biophysical indicators of land change dynamics.

2.1. Approaches to LULC Change Modeling

The dominant spatial modelling approaches identified in these studies indicate a shift in research orientation toward predictive methods based on spatial data and remote sensing (Marmion, 2009; Kamusoko, 2017; Antomi et al., 2023). Advances in high-resolution satellite imagery and the integration of machine learning algorithms have enabled the analysis of land-use change dynamics with greater accuracy than conventional statistical approaches. This trend suggests that LULC research is no longer merely descriptive but increasingly directed toward simulating and projecting future landscape change.

The most dominant methods are machine learning-based models, such as Random Forest, Support Vector Machine (SVM), Gradient Boosting, and various classification models used for land cover mapping and the prediction of change scenarios. Meanwhile, for dynamic change modelling, several studies have implemented Cellular Automata (CA), CA-Markov, or Multi-Layer Perceptron (MLP) to project built-up area expansion and land class transitions based on specific driving variables. In addition, process-based approaches, such as USLE, hydrological simulation, and erosion-runoff modelling, also appear in studies that explicitly assess soil degradation.

Several articles adopted multi-criteria decision-making methods, such as the Analytical Hierarchy Process (AHP) or landscape-based mitigation modelling, particularly in studies on flooding, erosion, and land degradation. These approaches were used to assign weights to driving factors and identify priority areas for mitigation. In general, the research trend shows two major streams: (1) Land change prediction modelling based on machine learning and satellite imagery, and (2) Soil degradation modelling based on physical processes or biophysical indices. The integration of these two approaches within a single modelling framework remains very limited. Most studies focus either on land change prediction or on soil degradation analysis as separate domains.

2.2. Variables Used

The parameters included in the studies reviewed here differ greatly but fall into three main categories: biophysical, anthropogenic, and environmental variables. Biophysical variables such as slope, elevation, distance to rivers and soil type, texture, bulk density, and SOC, together with vegetation indices NDVI (Normalized Difference Vegetation Index), NDBI (Normalized Difference Built-up Index), and MNDWI (Modified Normalized Difference Water Index). These variables are commonly used in both studies of soil degradation and of soil quality, especially with respect to changes in carbon content, susceptibility to erosion, and other forms of biophysical degradation.

Some commonly used anthropogenic variables include population density, distance to roads, distance to settlements, facility location, and indicators of development intensity. This is all the more important since these factors are dominant in LULC prediction studies of built-up area expansion. Environmental variables, on the other hand, include rainfall and temperature data, as well as soil moisture (water flow patterns) and other hydrological parameters that have been widely applied in erosion studies or hydrology-based degradation studies. In general, almost all articles use a mix of physical and anthropogenic variables, but, to our knowledge, only a few directly include soil quality variables in LULC prediction modeling. This has led to dynamic land changes being poorly integrated with indicators of soil degradation.

2.3. Implications for Soil Degradation

Of the 42 reviewed studies, most show that land-use change, specifically the conversion of natural land into built-up and intensive agricultural areas, leads to soil degradation in various forms. Higher erosion rates, reduced SOC, lower vegetation coverage, and loss of infiltration capacity are identified as the main impacts of land cover change in these articles. Hydrological modelling studies also show that increased runoff generation due to urbanization aggravates surface erosion, sediment yield, and slope instability. These results provide strong evidence of causation that soil degradation, through LULC dynamics, constitutes the main driver across different study areas.

Multiple publications further demonstrate that the effects of LULC change are not confined to physical degradation but also affect processes at higher levels (e.g., declines in soil ecological functions, reduced carbon storage capacity, increased susceptibility to floods and droughts). However, despite many of these relationships having been documented and studied, they are rarely integrated directly into a single unified LULC change prediction model alongside soil degradation indicators. The majority of studies measure soil degradation as an independent output rather than as a component of any long-term land change simulation. This indicates that the dynamic between anthropogenic expansion and soil health is still poorly understood.

3. Research Gaps

Cross-article synthesis highlights key research gaps. First, there is limited integration between LULC prediction modelling and soil degradation modelling. Most studies predict land change without linking it to soil degradation indicators, whereas soil degradation studies often rely on static land cover conditions without projecting how future changes may affect soil quality. This has resulted in a lack of studies capable of comprehensively capturing the dynamic interaction between the two. Systematic reviews specifically mapping the relationship between LULC change prediction and soil quality degradation indicators remain very limited in the scientific literature (Manandhar and Odeh, 2014; Delelegn et al., 2017; Yeneneh et al., 2024).

Second, soil quality variables such as SOC, bulk density, soil moisture, and other soil health indices are rarely used as driving variables in LULC modelling. In fact, soil quality may influence land conversion patterns, particularly in the context of agriculture and urbanization. Third, some studies still rely on traditional classification methods or simple regression, while the integration of deep learning and big data-based modelling remains limited. In addition, only a small number of studies examine land-use policy or soil-degradation mitigation scenarios, despite their strong relevance to spatial planning and soil conservation (Oliveira et al., 2018; Xiao et al., 2019; Geneletti, 2012).

Overall, the largest gap lies in the lack of a holistic approach capable of linking land change, soil biophysical processes, socio-economic variables, and policy scenarios within an integrated analytical framework (Kragt et al., 2009; Helming et al., 2011). This opens substantial opportunities for future research to develop predictive models capable of simultaneously simulating the spatial-temporal relationship between LULC dynamics and soil degradation.

Discussion

Key Points: The bibliometric review indicates that analysis of LULC change prediction has grown rapidly over the past two decades. The overall growth in publications indicates that the dynamics of land use change are increasingly recognized as a global strategic issue across environmental science. This emerges from a context of increasing pressure on land resources from urbanization, agricultural expansion, and climate change, which have heightened the demand for predictive frameworks to forecast landscape change.

Numerous advances in remote sensing technology, the integration of geographic information systems (GIS), and the development (and subsequent availability) of machine learning algorithms have extended research capacity to map multitemporal land cover change, as well as project future spatial dynamics with a higher accuracy than before (Wichansky et al., 2006; Koch et al., 2018; Maashi et al., 2025).

Keywords and research cluster analyses further show that spatial modelling and predictive analytics have emerged as the primary paradigm underpinning current LULC research. The prevalence of terms associated with remote sensing, GIS, land use change, and machine learning indicates that research has shifted away from simple descriptive frameworks towards more integrated, data-driven analytical paradigms.

This advancement enables researchers not only to describe the patterns of land-use change that already exist, but also to simulate potential landscape changes under various development scenarios and environmental pressures. Hence, LULC forecasting models are increasingly serving as a fundamental scientific tool that helps spatial planning, land resource management, and the formulation of environmental degradation mitigation strategies (Wang et al., 2022).

However, the identified cluster structure indicates that integrating LULC change prediction and soil degradation assessment remains underdeveloped. Studies focusing on spatial modelling generally emphasize the representation of land change and the analysis of its driving factors, whereas research on soil quality more often evaluates biophysical implications such as erosion, soil organic carbon loss, and reduced soil structural stability. These two streams of research have developed in parallel and have not yet formed an integrated analytical framework capable of simultaneously linking projected LULC change with soil degradation dynamics.

In fact, numerous studies have shown that land conversion is one of the main factors triggering soil degradation through increased erosion rates, changes in soil physical properties, and declines in organic matter content. Conversion of natural vegetation to intensive agricultural or built-up areas can reduce vegetation cover and increase soil susceptibility to surface erosion. In addition, such changes may affect the soil's capacity to store water and carbon, ultimately influencing ecosystem stability and the sustainability of soil functions as a provider of environmental services.

This integration gap indicates that the indicated LULC modeling for predicting future soil degradation risks has not yet been fully utilized as a decision-support tool. This means that predictive model systems need to be increasingly applied and multi-disciplinary, combining spatial modelling, hydrological and soil ecological aspects, and land-use policy. This integration can yield models that not only predict land cover change but also assess the ecological consequences of such changes. In this sense, predictive models may serve as reserves in the ground to detect areas of significant environmental vulnerability.

Also, how publications are distributed geographically is dominated by countries with research capacity, such as China and several first-world countries, whilst research in less developed regions is comparatively low. Some argue for more research attention with consideration of local biophysical and socio-economic contexts. There is considerable potential to develop more contextually relevant and responsive predictive models in areas experiencing intense pressure to change land use, if research can be strengthened in developing world regions.

In summary, this discussion strengthens these findings that LULC change prediction offers potential strategies not only to address environmental management issues but also to support sustainable land-use planning. Yet this potential will not be realized if land change modelling and soil degradation assessment are more tightly coupled. In the absence of such integration, predictive models may capture only a fragment of space (land change) but not the ecosystem signals that are critical to soil resources and sustainability.

This review adds to scientific knowledge by providing a systematic, high-resolution mapping of research developments in LULC change prediction and their relation to soil quality degradation, using bibliometric analysis and a systematic literature review. The analysis not only marks publication trends, collaboration networks, and methodological developments, but it also highlights a conceptual gap between land change modelling and soil degradation assessment approaches that have largely evolved in parallel in the scientific literature. These results set a theoretical foundation for integrating LULC prediction modelling and soil quality assessment within a unified research framework.

Rising to the challenge, an integrative approach would enhance the ability of models to assess and mitigate environmental degradation risks leading to better-informed land management decisions that are both adaptive and sustainable (Buenemann et al., 2011; Wang et al., 2023; Nambiar et al., 2025). As a consequence, future research directions are emphasized to increasingly articulate land change modelling and soil degradation assessment.

Future studies will be required to present analytic frameworks that systematically combine projected LULC change with soil quality degradation indicators. The synthesizing of explicit models by integrating multitemporal remote sensing data, GIS-based spatial analysis, and biophysical parameters, e.g., SOC, soil moisture, and erosion rate, can help to a greater extent in undertaking the ecosystem stability impacts resulting from land-use change (Peters et al., 2020; Xu et al., 2025; Zhang et al., 2025). Future studies should also broaden their scope to include developing regions, where land change dynamics are often intense but remain underrepresented in the scientific literature. A multi-disciplinary approach combining spatial modelling methods, soil ecological analysis, and land-use policy perspectives is expected to yield predictive models that not only describe landscape change but also support science-based decision-making for sustainable land resource management.

Conclusion

This systematic and bibliometric review shows that research on land use and land cover (LULC) change prediction has developed very rapidly over the past two decades. The dominance of approaches based on spatial modelling, remote sensing, and modern computational methods reflects a global research focus that remains focused on improving the accuracy of land change simulation and identifying patterns of spatial transformation.

This review systematically maps the relationship between LULC prediction research and soil quality degradation through bibliometric analysis and a systematic literature review, thereby providing a more comprehensive picture of research trends in this field.

The synthesis of the included articles confirms that LULC change is consistently associated with declining soil quality, as evidenced by increased erosion, loss of soil organic carbon, and weakened soil structural stability. However, these findings are still largely discussed as separate consequences rather than as components of an integrated modelling framework capable of simultaneously projecting land change and soil degradation. Therefore, there are important research gaps that require addressing, especially from a perspective of developing more robust and applicable models for environmental management.

This study shows that soil degradation processes require multi-disciplinary, integrated predictive models that combine spatial analyses, soil ecology related to environmental features, and the hydrological base for regional planning. Integrating such approaches can enhance the strategic role of LULC prediction as a supportive decision-making and adaptive land-use planning tool. Predictive models that identify complex pathways from land cover change to soil degradation indicators will better indicate the environmental impacts of landscape change.

In summary, this review covers the evolution of research on LULC change prediction and also identifies opportunities for integrating spatial modelling with soil quality assessment. In combination, these two aspects may represent an important foundation for future research and land management policies that are more transparent, sustainable, and responsive to environmental change.

References

Abad-Segura, E., Daniela, G.-Z.M. and Eloy, L.-M. 2022. Analysis of research on decision-making based on quantitative methods. *Revista de Metodos Cuantitativos para la Economia y la Empresa* 34:118-136, doi:10.46661/revmetodoscuanteconempresa.5135.

Abbood, R.A., Jafarzadeh, A.A., Oustan, S. and Hamad, A.I. 2025. Regional change prediction of land degradation risks using Cellular Automata-Markov modeling in Dhi Qar Province, Iraq. *Engineering, Technology and Applied Science Research* 15(3):22908-22914, doi:10.48084/etasr.10483.

Afuye, G.A., Nduku, L., Kalumba, A.M., Santos, C.G., Orimoloye, I.R., Ojeh, V., Thamaga, H.K. and Sibandze, P. 2024. Global trend assessment of land use and land cover changes: A systematic approach to future research development and planning. *Journal of King Saud University* 36(1), doi:10.1016/ j.jksus.2024.103262.

Ahmad, S., Farooq, R., Waseem, M. and Kohnová, S. 2025. How do land use changes affect temperature and groundwater in urban areas? An integrated remote sensing, and machine learning approach. *Advances in Space Research* 76(8):3963-3987, doi:10.1016/j.asr.2025.08.021.

Akhila, R. and Pramada, S.K. 2025. Land use land cover change detection and prediction using land change modeler – A case study of Kerala. *Journal of Earth System Science* 134, doi:10.1007/s12040-025-02594-2.

Alebachew, E.D. and Dengiz, O. 2025. Multi-criteria decision analysis and artificial neural network for assessing soil quality variation under different land use and land cover in Samsun, Türkiye. *Environmental and Sustainability Indicators* 27, doi:10.1016/j.indic. 2025.100737.

Al-Hashim, M.H., El-Sorogy, A.S., Alhejji, S.S. and Rikan, N. 2026. Assessing potentially toxic element contamination in agricultural soils of an arid region: A multivariate and geospatial approach. *Minerals* 16(1):93, doi:10.3390/min16010093

Alikhanova, S., Tarantino, C. and Bull, J.W. 2025. Tracking vegetation dynamics in drylands with MSAVI: Insights from the South Aral Sea. *Earth Systems and Environment*, doi:10.1007/s41748-025-00705-z.

Amin, M., Romshoo, S.A. and Ahmad, S.A. 2025. Assessment and monitoring of land degradation indicators and processes using a geospatial approach. *Modeling Earth Systems and Environment* 11(1), doi:10.1007/s40808-024-02262-2.

Ansar, Z. and de Vries, W.T. 2024. Urban sprawl symptoms in Bandar Lampung Suburban Area, Indonesia. *Geoplanning* 11:205-222, doi:10.14710/ geoplanning.11.2.205-222.

Antomi, Y., Koestoer, R.H., Arif, D.A., Hidayat, H. and Angraina, D. 2023. Using geographic information system technology for land-use modelling on developing area of Tanah Datar Sumatera Barat. *TEM Journal* 12(1):167-174, doi:10.18421/TEM121-22.

Aregaw, Y., Suryabhagavan, K.V. and Kassawmar, T. 2025. Comprehensive land degradation assessment using geospatial modeling approach, the Case of Dega Damot District, Northwestern Ethiopia. *Applied and Environmental Soil Science* 2025(1):6696976, doi:10.1155/aess/6696976.

Arifin, S., Anandha, Y.V.A., Setiawan, E., Phoebus, T.D., Jonathan, S., Effendi, M., Setyawan, M.E. and Putra, K.L.O. 2023. Prospects and possibilities for future research of Fuzzy C-Means (FCM). *International Journal of Intelligent Systems and Applications in Engineering* 11(2):741-751.

Arsyad, U., Amaliah, R. and Dahlan, N.A. 2024. Analysis of land cover changes as one of the quality indicators of the Biang Loe River Watershed. *IOP Conference Series: Earth and Environmental Science* 1430(1), doi:10.1088/1755-1315/1430/1/012010.

Asmoay, A., Shams, E. and Sawires, R. 2026. Integrated assessment of soil and groundwater quality, irrigation suitability, and land-use dynamics in the reclaimed lands of West Mallawi, Egypt. *CLEAN - Soil Air Water* 54, doi:10.1002/clen.70092.

Beroho, M., Briak, H., Cherif, E.K., Boulahfa, I., Ouallali, A., Mrabet, R., Kebede, F., Bernardino, A. and Anoumaria, K. 2023. Future scenarios of land use/land cover (LULC) based on a CA-Markov simulation model: case of a Mediterranean watershed in Morocco. *Remote Sensing* 15(4):1162, doi:10.3390/rs15041162.

Bîrsănuc, E.-M., Man, T.-C. and Petrea, D. 2019. What does unsustainable urban sprawl bring? Spatial patterns analysis of built environment in Cluj metropolitan area. *Journal of Settlements and Spatial Planning* 10(2):121-130, doi:10.24193/JSSP.2019.2.05

Boroughani, M., Naemi, M., Pourhashemi, S., Asadi, Zangane, M.A., Al-Hemoud, A. and Al-Qadeeri, G. 2026. Linking dust source susceptibility mapping and land use change in Middle East. *Atmospheric Pollution Research* 17(2):102774, doi:10.1016/j.apr. 2025.102774.

Buenemann, M., Martius, C., Jones, J.W., Herrmann, S.M., Klein, D., Mulligan, M., Reed, M.S., Winslow, M., Washington-Allen, R.A., Lal, R. and Ojima, D. 2011. Integrative geospatial approaches for the comprehensive monitoring and assessment of land management sustainability: Rationale, potentials, and characteristics. *Land Degradation and Development* 22(2):226-239, doi:10.1002/ldr.1074

Chan, C. and Nurrosyidah, A. 2025. Democratizing Artificial intelligence for social good: A bibliometric–systematic review through a social science lens. *Social Sciences* 14(1), doi:10.3390/socsci14010030.

Che, L., Guo, S. and Deng, Y. 2025. Land use evolution and prediction: a bibliometric review. International *Journal of Environmental Science and Technology* 22(12):11077-11090, doi:10.1007/s13762-024-05983-0.

Cheng, P., Tang, H., Dong, Y., Liu, K., Jiang, P. and Liu, Y. 2021. Knowledge mapping of research on land use change and food security: A visual analysis using Citespace and Vosviewer. *International Journal of Environmental Research and Public Health* 18(24), doi:10.3390/ijerph182413065.

Cherigui, A., Talia, A., Benstaali, I., Blissag, B., Zerouali, B. and Meddi, M. 2025. Urban expansion and its environmental impacts in northwestern Algeria using cellular automata-Markov-chain modeling. *Modeling Earth Systems and Environment* 11:159, doi:10.1007/s40808-025-02309-y

Choudhary, K., Boori, M.S. and Kupriyanov, A. 2018. Spatial modelling for natural and environmental vulnerability through remote sensing and GIS in Astrakhan, Russia. *Egyptian Journal of Remote Sensing and Space Science* 21(2):139-147, doi:10.1016/j.ejrs.2017.05.003.

da Vitória, M.R., Farias, R., Paranhos, H., de Souza Bezerra, I. and de Sousa Júnior, R.P. 2018. Case study about erosion in Elmo Serejo Avenue, Taguatinga/

Federal District–Brazil. In: *Numerical Analysis of Nonlinear Coupled Problems* (287-301). Springer International Publishing, doi:10.1007/978-3-319-61905-7_25.

Delcourt, N., Farnet-Da Silva, A.-M., Rébufa, C., Perissol, C. and Dupuy, N. 2023. Does land use legacy matter for current soil functioning? A bibliometric study (2001-2020). *Environmental Reviews* 31(1):168-181, doi:10.1139/er-2021-0128.

Delelegn, Y.T., Purahong, W., Blazevic, A., Yitaferu, B., Wubet, T., Göransson, H. and Godbold, D.L. 2017. Changes in land use alter soil quality and aggregate stability in the highlands of northern Ethiopia. *Scientific Reports* 7(1), doi:10.1038/s41598-017-14128-y.

Dengiz, O., Alaboz, P., Saygın, F., Sargın, B. and Karaca, S. 2026. An artificial intelligence approach to the assessment and prediction of soil quality dynamics. *Communications in Soil Science and Plant Analysis* 57(2):352-368, doi:10.1080/00103624.2025.2593967.

Desalegn, M.Y., Miheretu, B.A. and Gobezie, T. 2025. Impact of land use/land cover changes on soil erosion risk in upper Mile River sub-watershed, North Eastern highlands of Ethiopia. *Geology, Ecology, and Landscapes* 9(2):463-475, doi:10.1080/24749508.2023.2206063.

Doubleday, K., Oleskewicz, K., Ovaitt, S., Hickey, T., Herbert, S.J. and Macknick, J. 2025. Impacts of year-to-year weather variability and inter-panel spacing on agrivoltaic crop yields in Massachusetts. *Agrofestry Systems* 99:152, doi:10.1007/s10457-025-01248-y.

Dutta, B., Srivastva, P.K. and Boruah, A. 2025. Identification of soil erosion susceptible areas using fuzzy logic and hydrological indices aided by mineralogical-granulometric analysis in lower Subansiri basin, Assam, India. *Environmental Earth Sciences* 84:70, doi:10.1007/s12665-025-12087-6

Erfanian, M.B., Barahoei, H., Zeynali, M.M. and Mirshamsi, O. 2025. Employing habitat suitability modeling to assess the distribution and envenomation potential of scorpion species in Iran. *Journal of Medical Entomology* 62(2):337-346, doi:10.1093/jme/tjae151.

Ferreira, C.S.S., Walsh, R.P.D. and Ferreira, A.J.D. 2018. Degradation in urban areas. *Current Opinion in Environmental Science and Health* 5:19-25, doi:10.1016/j.coesh.2018.04.001.

Geneletti, D. 2012. Environmental assessment of spatial plan policies through land use scenarios. A study in a fast-developing town in rural Mozambique. *Environmental Impact Assessment Review* 32(1):1-10, doi:10.1016/j.eiar.2011.01.015.

Giandon, P., Vinci, I., Obber, S., Di Leginio, M. and Rischia, I. 2010. Development of environmental indicators for Italian soils. *Fresenius Environmental Bulletin* 9(8B):1741-1748.

Hasanuzzaman, M., Adhikary, P.P. and Shit, P.K. 2025. Integrated DSAS and CA–Markov model approach for assessing gully erosion dynamics and land use transformations: evidence from Chotanagpur plateau region, Eastern India. *Proceedings of the Indian National Science Academy*, doi:10.1007/s43538-025-00660-3.

Hassan, F.A., Oluwasemire, K.O. and Elmobarak, A.E.A. 2025. Modelling the spatial distribution of drought effects on land degradation in the Blue Nile Region, Sudan. *Journal of Applied and Natural Sciences* 17(3):1341-1265, doi:10.31018/jans.v17i3.6608.

Helming, K., Diehl, K., Bach, H., Dilly, O., König, B., Kuhlman, T., Pérez-Soba, M., Sieber, S., Tabbush, P., Tscherning, K., Wascher, D. and Wiggering, H. 2011. Ex ante impact assessment of policies affecting land use, Part A: Analytical framework. *Ecology and Society* 16(1), doi:10.5751/ES-03839-160127.

Hu, L., Duan, X. and Liu, J. 2026. Application and assessment of a CA-ANN model for land use change simulation and multi-temporal prediction in Guiyang City, China. *Sustainability (Switzerland)* 18(3), doi:10.3390/su18031518.

Hussain, S., Qaisrani, S.A., Tariq, A., Mubeen, M. and Ullah, S. 2025. Assessing past, present, and simulated future prediction of land use land cover changes using CA-Markov chain models with Satellite data. *Results in Engineering* 26, doi:10.3390/su18031518.

Irawan, P. and Setiawan, J. 2025. Forecasting the long-term impacts of land use and cover changes on runoff coefficient and flood hydrograph: a case study of the Upper Citanduy Basin, Indonesia. *Journal of Degraded and Mining Lands Management* 12(3):7417-7429, doi:10.15243/jdmlm.2025.123.7417.

Jawarneh, R.N., Abulibdeh, A., Hashem, N., Awawdeh, M., Al-Awadhi, T., Abdullah, M.M. and El Kenawy, A.M. 2024. 2024. Assessing and predicting land cover dynamics for environmental sustainability in Jordan's arid ecosystems using CA-Markov model. *Remote Sensing Applications: Society and Environment* 35:101262, doi:10.1016/j.rsase.2024.101262.

Jukneliené, D., Narmontiené, V., Valčiukiené, J. and Mozgeris, G. 2025. Driving forces of agricultural land abandonment: A Lithuanian case. *Land* 14(4):899, doi:10.3390/land14040899.

Kah, M., Faye, C., Mbaye, M.L., Yalo, N. and Gunnar, L. 2025. Hydroclimatic trends and land use changes in the continental part of the Gambia River Basin: Implications for water resources. *Water* 17(14):2075, doi:10.3390/w17142075.

Kamran, J.G., Musa, K.K. and Sadegh, G.F. 2020. An investigation into urban development: Patterns with sprawl and other corresponding changes: A case study of Babol City. *Journal of Urban Culture Research* 20:26-43, doi:10.14456/jucr.2020.2.

Kamusoko, C. 2017. Importance of Remote Sensing and Land Change Modeling for Urbanization Studies. In:Urban Book Series (pp. 3-10), doi:10.1007/978-981-10-3241-7_1.

Khan, F., Zaman, F., Qu, Y., Wang, J., Darmorakhtievich, O.H., Wu, Q., Fahad, S., Du, F. and Xu, X. 2025. Long-term effects of crop treatments and fertilization on soil stability and nutrient dynamics in the Loess Plateau: Implications for soil health and productivity. *Sustainability* 17(3):1014, doi:10.3390/su17031014

Koch, J., Wimmer, F. and Schaldach, R. 2018. Analyzing the relationship between urbanization, food supply and demand, and irrigation requirements in Jordan. *Science of The Total Environment* 636:1500-1509, doi:10.1016/j.scitotenv.2018.04.058.

Kragt, M.E., Newham, L.T.H. and Jakeman, A.J. 2009. A Bayesian Network approach to integrating economic and biophysical modelling. *18th World IMACS Congress and MODSIM 2009 - International Congress on Modelling and Simulation: Interfacing Modelling and Simulation with Mathematical and Computational Sciences, Proceedings* 2377-2383.

Lari, M., Nazarisamani, A., Tariq, A., Jondani, S.A. and Rebouh, N.Y. 2025. Quantifying sediment yield and discharge fluctuations using the GeoWEPP in response to soil and water conservation practices. *International Journal of Sediment Research* 41(2), doi:10.1016/j.ijsrc.2025.11.005.

Leta, M.K., Demissie, T.A. and Tränckner, J. 2021. Modeling and prediction of land use land cover change dynamics based on land change modeler (LCM) in Nashe watershed, Upper Blue Nile basin, Ethiopia. *Sustainability (Switzerland)* 13(7), doi:10.3390/su13073740.

Li, J. and Wei, R. 2022. VOSviewer application status and its knowledge base. *Journal of Library and Information Science in Agriculture* 34(6):61-71, doi:10.13998/j.cnki.issn1002-1248.21-0843.

Li, S., Liu, X., Li, X. and Chen, Y. 2017. Simulation model of land use dynamics and application: Progress and prospects. *Yaogan Xuebao/Journal of Remote Sensing* 21(3):329-340, doi:10.11834/jrs.20176159.

Li, Z., Qin, W., You, Y., Chen, J., Zhao, X., Dong, R., Gu, X., Cui, S., Chen, C., Stirling, E. and Xue, R. 2025. Land use patterns change N and P cycling bacterial diversity in an acidic karst soil. *Agriculture Ecosystems and Environment* 380, doi:10.1016/j.agee.2024.109389.

Liu, J., Ren, Y., He, P. and Xiao, J. 2025. Quantifying uncertainty in projections of desertification in Central Asia using Bayesian Networks. *Remote Sensing* 17(4):665, doi:10.3390/rs17040665.

Liu, L., Yu, S., Zhang, H., Wang, Y. and Liang, C. 2023. Analysis of land use change drivers and simulation of different future scenarios: Taking Shanxi Province of China as an example. *International Journal of Environmental Research and Public Health* 20(2), doi:10.3390/ijerph20021626.

Liwur, S.B., Adam A.R. and Tagnan, J.N. 2026. After the flames and smoke, then what? Spatial analysis and heterogeneity modeling of bushfire effects on vegetation health and air quality in Ghana. *Remote Sensing Applications: Society and Environment* 41:101854, doi:10.1016/j.rsase.2025.101854.

Maashi, M., Alzaben, N., Negm, N., Veeramani, V., Begum, S.S. and Palaniappan, G. 2025. Forecasting land use changes in crop classification and drought using remote sensing. *Journal of Arid Land* 17(5):575-589, doi:10.1007/s40333-025-0013-y.

Manandhar, R. and Odeh, I.O.A. 2014. Interrelationships of land use/cover change and topography with soil acidity and salinity as indicators of land degradation. *Land* 3(1):282-299, doi:10.3390/land3010282.

Marmion, M. 2009. New insights into the uncertainty of spatial models in physical geography. *Nordia Geographical Publications* 38(1):1-49.

Mosleh, M.K. 2025. Integrating the CA–Markov model and geospatial techniques for spatiotemporal prediction of land use/land cover dynamics in Qus District, Egypt. *Modeling Earth Systems and Environment* 11(5), doi:10.1007/s40808-025-02479-9.

Mselle, B.D., Zsembinszki, G., Borri, E., Vérez, D. and Cabeza, L.F. 2021. Trends and future perspectives on the integration of phase change materials in heat exchangers. *Journal of Energy Storage* 38, doi:10.1016/j.est.2021.102544.

Muhammad, R., Zhang, W., Abbas, Z., Guo, F. and Gwiazdzinski, L. 2022. Spatiotemporal change analysis and prediction of future land use and land cover changes using QGIS MOLUSCE plugin and remote sensing big data: A case study of Linyi, China. *Land* 11(3), doi:10.3390/land11030419.

Mungai, L M., Djenontin, I.N.S., Zulu, L.C. and Messina, J.P. 2025. Spatial-temporal modeling of land-use dynamics at the agricultural-forest interface: insights from Ntchisi District, Malawi. *Remote Sensing Applications: Society and Environment* 38:101597, doi:10.1016/j.rsase.2025.101597.

N'Danikou, K.A., Wédjangnon, A.A., Hounton, C.C. and Ouinsavi, C.A.I.N. 2025. Change monitoring and assessment of land use and land cover for the municipality of Ouessè in Benin by the modules for land use change evaluation plugin. *International Journal of Agricultural and Environmental Information Systems* 16(1):18, doi:10.4018/IJAEIS.369814,

Nahid, S., Kumar, R.P., Acharya, P., Kumar, K. and Purohit, S. 2025. Forecasting urban expansion in Delhi-NCR: integrating remote sensing, machine learning, and Markov chain simulation for sustainable urban planning. *GeoJournal* 90(2), doi:10.1007/s10708-025-11317-5.

Nakajima, T. 2019. Soil health and carbon sequestration in Urban farmland. In*: Recycle Based Organic Agriculture in a City* (pp. 147–158), doi:10.1007/978-981-32-9872-9_7.

Nambiar, A., Firoz, C.M. and Krishnan, V.S. 2025. Towards sustainable land management: A regional perspective for a comprehensive Land Degradation Assessment. *Land Use Policy* 158, doi:10.1016/j.landusepol.2025.107696.

Nardotto Júnior, A.O., Pires, F.R., Santos, A.R. and Neves, L.Z. 2026. Land conservation based on land use potential and erosion risk in an Atlantic Forest watershed (Brazil). *Ecological Indicators* 183, doi:10.1016/j.ecolind.2026.114683.

Oliveira, E., Tobias, S. and Hersperger, A.M. 2018. Can strategic spatial planning contribute to land degradation reduction in urban regions? State of the art and future research. *Sustainability (Switzerland)* 10(4), doi:10.3390/su10040949.

Peters, D., Niemann, O. and Skelly, R. 2020. Remote sensing of ecosystem structure: Fusing passive and active remotely sensed data to characterize a deltaic wetland landscape. *Remote Sensing* 12(22):1-25, doi:10.3390/rs12223819.

Putra, A.N., Nita, I., Wicaksono, K.S., Prasetya, N.R., Sugiarto, M.T., Hidayat, F., Alim, Z., Sartono, S.E., Sasangka, P.G., Kusuma, T.R., Abbasi, B., Gessert, A., Hasmadi, M.M.H. and Khokthong, W. 2025. Potential erosion and sedimentation based on land use change by using cellular automata-artificial neural network. *Geomatics, Natural Hazards and Risk* 16(1):2461058, doi:10.1080/19475705.2025.2461058.

Rahmanipour, F., Marzaioli, R., Bahrami, H.A., Fereidouni, Z. and Bandarabadi, S.R. 2014. Assessment of soil quality indices in agricultural lands of Qazvin Province, Iran. *Ecological Indicators* 40:19-26, doi:10.1016/j.ecolind.2013.12.003.

Ramachandra, T.V., Negi, P., Mondal, T. and Setturu, B. 2025. Sustainable management of natural resources at disaggregated levels with insights from landscape dynamics. *Forum Geografi* 39(2):136-162, doi:10.23917/forgeo.v39i2.6857

Ren, Y., Lü, Y., Comber, A., Fu, B., Harris, P. and Wu, L. 2019. Spatially explicit simulation of land use/land cover changes: Current coverage and future prospects. *Earth-Science Reviews*190:398-415, doi:10.1016/j.earscirev.2019.01.001.

Richiedei, A., Giuliani, M. and Pezzagno, M. 2025. Sub-regional biophysical and monetary evaluation of ecosystem services: An experimental spatial planning implementation. *Land* 14(2):216, doi:10.3390/ land14020216.

Rischia, I., di Leginio, M., Fumanti, F., Giandon, P., Obber, S. and Vinci, I. 2010. Environmental indicators for Italian soils (Sias project): Development of a new approach from regional to harmonised national data. *Italian Journal of Agronomy* 5(SUPPL. 3):103-107, doi:10.4081/ija.2010.s3.103.

Rivera-Fernandez, A.S., Cotrina-Sanchez, A., López, S.R., Zabaleta-Santisteban, J.A., Ramírez, R.N., Medina-Medina, A.J., Tuesta-Trauco, K.M., Sánchez-Vega, J.A., Silva-Melendez, T.B., Oliva-Cruz, M., Portocarrero, C. and Barboza, E. 2025. Spatiotemporal land cover change and future hydrological impacts under climate scenarios in the Amazonian Andes: A case study of the Utcubamba River Basin. *Land* 16(6):1234, doi:10.3390/ land14061234.

Riyanto, I.A., Hendrayana, H., Widyaningsih, Y., Jayanto, G.D., Nuha, A. and Sumartono, S. 2025. The decline in water level and discharge of Lake Toba of North Sumatera, Indonesia, affected by land degradation. *Journal of Degraded and Mining Lands Management* 12(2):7123-7140, doi:10.15243/jdmlm.2025.122.7123.

Saavedra, M., Muñuzuri, A.P., Menendez, M. and Balsa-Barreiro, J. 2024. Analysing macroscopic traffic rhythms and city size in affluent cities: insights from a global panel data of 25 cities. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 382, doi:10.1098/ rsta.2024.0102.

Sabitha, N.M., Thampi, S.G. and Sathish, K.D. 2025. Estimation of potential impact of land use change on sediment yield from a small tropical watershed using the TREX erosion model. *Land Degradation & Development* 36(3):853-871, doi:10.1002/ldr.5398.

Samaei, F., Emami, H. and Lakzian, A. 2022. Assessing soil quality of pasture and agriculture land uses in Shandiz county, northwestern Iran. *Ecological Indicators* 139, doi:10.1016/j.ecolind.2022.108974.

Senthilkumar, S., Alabdulkreem, E. and Alruwais, N.M.K. 2025. Coastal spatial planning using object-based image analysis and image classification techniques. *Journal of South American Earth Sciences* 152:105322, doi:10.1016/j.jsames.2024.105322.

Shahidehpour, M., Li, Z. and Ganji, M. 2018. Smart cities for a sustainable urbanization: Illuminating the need for establishing smart urban infrastructures. *IEEE Electrification Magazine* 6(2):16-33, doi:10.1109/ MELE.2018.2816840.

Singh, D.K., Kumar, A., Suri, D., Kumar, P., Sharma, R. and Sood, N. 2024. Artificial intelligence in gaming: A bibliometric analysis of research outputs and trends. 2024 *International Conference on Integration of Emerging Technologies for the Digital World, ICIETDW* 2024, doi:10.1109/ICIETDW61607.2024. 10939117.

Sitompul, H., Saifi, M. and Hutahayan, B. 2024. Use of renewable energy to enhance firm performance: A systematic review. *Sustainability (Switzerland)* 16(21), doi:10.3390/su16219157.

Sun, Q., Huang, L., Meng, H., Chi, L., Wu, J. and Zhou, X. 2025. Review of simulations on land use change: a methodology based on bibliometric analysis. *Frontiers in Sustainable Food Systems* 9, doi:10.3389/fsufs.2025.1548565.

Supangkat, S.H. 2018. Big data analytics for safe and secure city. *Proceedings - 2018 International Conference on ICT for Smart Society: Innovation Toward Smart Society and Society* 5.0, doi:10.1109/ICTSS.2018.8550023.

Suprayogi, M.N. 2024. Bridging gaps in learning: Tracing the trends of differentiated instruction in higher education. *9th International Conference on Business and Industrial Research, Proceedings* 373-378, doi:10.1109/ICBIR61386.2024. 10875687.

Szatmári, G., Laborczi, A., Takács, K., Mészáros, J., Koós, S., Bakacsi, Z. and Pásztor, L. 2026. HU-SoilCarbonGrids: An initiative for providing comprehensive information on soil organic carbon changes in Hungary. *European Journal of Soil Science* 77(1):e70292, doi:10.1111/ejss.70292.

Tamiru, B., Soromessa, T., Warkineh, B. and Feyisa, G.L. 2025. Effect of structural variation in selected woody species on selected soil chemical properties in the Mountain of Hangadi Watershed, Genale Dawa Basin, Ethiopia. *Applied and Environmental Soil Science* 2025(1):5217558, doi:10.1155/aess/5217558.

Teku, D., Sisay, T., Ali, A. and Ayalew, A. 2026. Optimizing flood hazard zonation and planning landscape-based mitigation measures in Gimba Sub Watersheds, Northeastern Ethiopia: A comprehensive approach. *Journal of Flood Risk Management* 19(1):e70172, doi:10.1111/jfr3.70172.

Thakur, P.K., Verma, R.K. and Pradhan, B. 2026. Integrating CA–Markov–ANN for spatiotemporal prediction of land use dynamics in a fragile Himalayan watershed. *Remote Sensing Applications: Society and Environment* 41, doi:10.1016/j.rsase.2025.101856.

Thakur, T.K., Patel, D.K., Thakur, A. and Arora, N.K. 2025. Evaluation of land degradation vulnerability in coal mined areas of Madhya Pradesh, India using geospatial and AHP modeling: a 40-year assessment and eco-restoration of degraded landscape. *Environmental Sustainability* 7:17, doi:10.1007/s42398-025-00347-x.

Verburg, P.H. 2014. The representation of human-environment interactions in land change research and modelling. In: *Understanding Society and Natural Resources: Forging New Strands of Integration Across the Social Sciences*, doi:10.1007/978-94-017-8959-2_8.

Verburg, P.H., Bakker, M., Overmars, K.P. and Staritsky, I. 2008. Landscape level simulation of land use change. In: *Sustainability Impact Assessment of Land Use Changes* (pp. 211-227), doi:10.1007/978-3-540-78648-1_11.

Wang, J., Bretz, M., Akber, M.A. and Aghajani, M. 2022. Machine learning in modelling land-use and land cover-change (LULCC): Current status, challenges and prospects. *Science of The Total Environment* 822:153559, doi:10.1016/j.scitotenv.2022.153559.

Wang, Y., Lü, Y., Lü, D., Yin, L. and Wang, X. 2023. An integrative methodology framework for assessing regional ecological risk by land degradation using the case of the Qinghai-Tibet Plateau. *Environmental Research Letters* 18(11), doi:10.1088/1748-9326/ad03a1.

Wedajo, G.K. 2025. Land Use/Land Cover Changes, Drivers, and Implications. In: *Springer Geography* Vol. Part F762 (pp. 235-259), doi:10.1007/978-3-031-65241-7_10.

Wei, F. and Jiang, Y. 2025. Multi-scenario simulation analysis of land use change in Hangzhou using the SD-PLUS model. *Journal of Agricultural Resources and Environment* 42(1):44-56, doi:10.13254/ j.jare.2023.0818.

Weng, X., Zhang, H., Zhu, J., Wang, D., Wang, S., Mei, Y. and Luo, M. 2025. Unveiling divergent trends in soil erosion and soil organic carbon displacement in response to climate and land-use changes over China. *Earth Interactions* 29, doi:10.1175/EI-D-24-0002.1.

Wichansky, P.S., Weaver, C.P., Steyaert, L.T. and Walko, R.L. 2006. Evaluating the effects of historical land cover change on summertime weather and climate in New Jersey. In: *New Jersey's Environments: Past, Present, and Future* (Vol. 9780813539225, pp. 128-163).

Xiao, Y., Xiong, Q. and Pan, K. 2019. What is left for our next generation? Integrating ecosystem services into regional policy planning in the three gorges reservoir area of China. *Sustainability (Switzerland)* 11(1), doi:10.3390/su11010003.

Xu, R., Fan, Y., Fan, B., Feng, G. and Li, R. 2025. Classification and monitoring of salt marsh vegetation in the Yellow River delta based on multi-source remote sensing data fusion. *Sensors* 25(2), doi:10.3390/s25020529.

Yameogo, J.T., Sanon, Z., Moussa, B.M., Somda, I., Lykke, A.M. and Axelsen, J.A. 2019. Physicochemical indicators of land degradation in Burkina Faso. *International Journal of Biological and Chemical Sciences* 13(4):2421-2432, doi:10.4314/ijbcs.v13i4.43.

Yan, H., Zeng, J., Lu, X. and Zhao, F. 2025. Analysis and prediction of spatial and temporal variation of carbon storage in limestone area in recent 30 years:A case study of the Hongshui River Basin. *Carsologica Sinica* 44(1):100-112, doi: 10.11932/karst20250107.

Yeneneh, N., Elias, E. and Feyisa, G.L. 2024. Monitoring soil quality of different land use systems: a case study in Suha watershed, northwestern highlands of Ethiopia. *Environmental Systems Research* 13(1), doi:10.1186/s40068-024-00336-9.

Yesuf, Y. and Fields, Z. 2025. Artificial intelligence adoption as a driver of innovation and competitiveness in SMEs: A bibliometric and systematic review. *F1000Research* 14, doi:10.12688/f1000research.171494.1.

Zhang, Y., Lin, X., Hei, J., Wang, Y. and Zhang, A. 2025. Multiscale remote sensing methods for monitoring wetland ecosystem dynamics and crop development. *Frontiers in Environmental Science* 13, doi:10.3389/fenvs.2025.1626025.

Zhang, Z., Liu, G., Qiang, F., Liu, C. and Ai, N. 2026. Effect of environmental factors on soil quality across various land-use types in the water-wind erosion crisscross region of China's Loess Plateau. *Journal of Forestry Research* 37(1), doi:10.1007/s11676-025-01956-2