Leveraging Spatial Analysis for Sustainable Land Use Change Management: A Case of the Mountain Elgon Region

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Abstract: Anthropogenic activities such as agriculture, deforestation and expansion of infrastructure have significantly changed land use land cover. These changes have raised environmental concerns, including soil erosion, landslides, water-catchment degradation and loss of biodiversity, with adverse consequences for food production and thus livelihoods. This study sought to explore how the associations between slope, elevation, distance to roads and rivers, population growth and hillshade influence spatial and temporal variations in land use change. The methodology involved integrating remote sensing, geographic information systems and spatial modelling. The study found that deforestation is a persistent phenomenon, with forest cover falling from 32.34% (2014) to 14.40% (2054). Similarly, the rangeland coverage is projected to decrease significantly from 17.74% in 2014 to 8.91% in 2054.Urbanization, on the other hand is rapidly increasing, tripling from 18.27% in 2014 to 48.55% in 2054. It has been shown that population growth, distance from roads, elevation and slope are strongly correlated, with the latter being very strong. Among the identified potential synergies, built up areas are expected to almost reach 50% by 2054 at the expense of deforestation, land degradation and water loss. Based on the identified synergies, it is recommended that a balance between economic growth and environmental sustainability be sought to promote land use change management.

1 INTRODUCTION

Over the years, anthropogenic activities have significantly altered land use and land cover (LULC) (Ojelabi et al., 2025). These changes have triggered environmental concerns, including soil erosion, landslides, water catchment degradation, and biodiversity loss (Aduku et al., 2024), and have had undesirable effects on food production, thus threatening livelihoods, especially in developing countries (Luwa et al., 2024). These changes have incited global debate as they directly affect sustainable development and human well-being (Aduku et al., 2024).

Spatial analysis, GIS, and remote sensing support informed land use decisions by revealing connections across sectors and balancing environmental, social, and economic priorities. This approach supports the integration of geographic data, predictive modeling, and decision support tools, thereby advancing planning, policymaking, and sustainability efforts (Bielecka, 2020).

Additionally, spatial analysis provides geographic specificity, enhancing the realism of models by incorporating factors such as topography, climate, and infrastructure (Oztuna, 2023). Consequently, extensive research has been undertaken at various spatial and temporal scales for diverse purposes highlighting the essential role of spatial analysis in land use change management.

Between 1987 and 2015 in Côte d'Ivoire, 1.44% of forestland and 3.44% of dense forest were converted to agricultural and degraded forest areas, respectively (Kouassi et al., 2021). In Ethiopia, cultivated and settlement areas increased by 6.4% and

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6.5%, while grassland and forest cover are projected to decline by 22.3% and 63.8% by 2050 (Mathewos et al., 2022). Similarly, urban areas in Southwestern Nigeria expanded from 341.7 km² to 520.6 km² between 1984 and 2019 (Fashe et al., 2020). These rapid LULC changes pose major challenges to sustainable development, affecting forest cover, increasing flood risks, complicating urban planning, and straining agriculture and water resources (Akinyemi, 2021).

In Uganda's Mt. Elgon region, various studies have addressed LULC dynamics. Luwa et al. (2020) used intensity analysis to assess change patterns; Opedes et al. (2022) examined land cover change and subsistence farming; and Bamutaze et al. (2021) evaluated erosion risk via Global Positioning System data. However, these studies explicitly underscored the associations between population growth, proximity to rivers, proximity to roads, slope, digital elevation model (DEM), hill shade, and aspect. This study explored how the associations between these factors influence spatial and temporal variations in land use change.

2 MATERIALS AND METHODS

2.1 Study Area

The study was conducted in Mbale, Bududa, Manafwa and Namisindwa (Figure 1). The study area is positioned between 0°40'0"N and 1°10'0"N latitude and 34°10'0"E and 34°30'0"E longitude. The region encompasses a total area of 320 km² with a population of approximately 1,338,178 people. The topography, climatic conditions and socio-economic activities provide a complex context for analysing LULC changes, making ideal setting for this research.

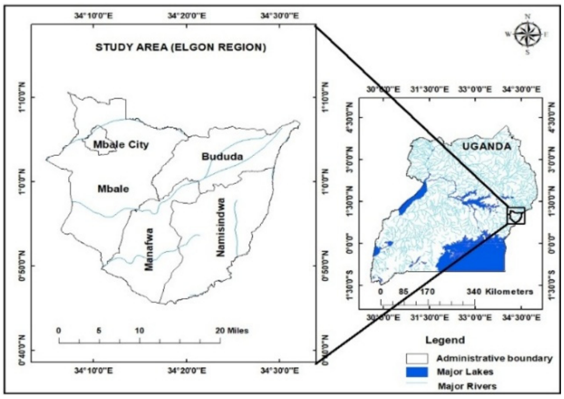

Figure 1: The Study Area.

The methodological approach integrates remote sensing with geographic information systems (GIS) to assess LULC dynamics in the region.

2.2 Data Collection

2.2.1 Satellite Imagery

Multi-temporal satellite images from Landsat 8, with a spatial resolution of 30 m, were acquired from the United States Geological Survey (USGS) Earth Explorer (https://earthexplorer.usgs.gov/) for the years 2014, 2019 and 2024. The imagery was chosen based on phenological considerations, seasonality and minimal cloud cover to ensure precise analysis.

2.2.2 Cramer's V Analysis of Driver Variables

To evaluate the strength of association between selected drivers and LULC changes, Cramer's V values were computed using the R-Processing plugin in QGIS. Cramer's V, ranging from 0 (no association) to 1 (strong association), quantifies relationships between categorical variables. This analysis revealed how spatial factors such as population growth, proximity to rivers and roads, slope, elevation (DEM), and hillshade contribute to LULC dynamics. The results highlighted which variables most strongly influenced land use changes in the Mount Elgon region.

2.2.3 Ancillary Data

Roads and rivers were derived from OpenStreetMap (http://www.openstreetmap.org/), providing essential infrastructure data. Population growth data were sourced from WorldPop (http://www.worldpop.org), offering insights into demographic pressures.

2.3 Data Pre-processing

2.3.1 Geometric Correction

Geometric correction was conducted on all satellite images to ensure spatial alignment using reference layers such as DEM, slope, and distance from roads. The correction process utilized the MOLUSCE plugin in QGIS to preserve data consistency across temporal layers.

2.3.2 Image Classification

A supervised classification technique, specifically the maximum likelihood algorithm within ArcGIS, was employed to categorize LULC types. Training samples were selected based on expert knowledge and field validation, ensuring the accuracy of the classification process. To assess the reliability of the classified maps, their accuracy was evaluated using a confusion matrix and kappa coefficient, comparing the classified outputs with ground-truth data. This approach ensured a robust validation of the classification results.

2.4 Analysis of Spatial and Temporal Variations

2.4.1 Land Use Change Detection

The LULC maps for 2014, 2019, and 2024 were analyzed to detect spatial and temporal changes. The MOLUSCE plugin in QGIS was used for change detection, specifically employing post-classification comparison to identify transitions among different LULC categories over time. This method was chosen because it allowed for accurate identification of land use changes by comparing classified maps from different years, making it ideal for assessing spatial dynamics and temporal trends in LULC.

2.4.2 Spatial Variable Analysis

This study examined how factors such as DEM, slope, proximity to rivers and roads, and population influenced land use change in the Mount Elgon region. DEM and slope determine land suitability by identifying areas vulnerable to erosion and landslides, thereby guiding human activities. Proximity to rivers impacts agriculture and settlement patterns due to water availability and flood risk, while proximity to roads drives urban expansion, agricultural development, and resource extraction. Population growth increases the demand for farmland and settlements. Together, these factors shape the spatial and temporal dynamics of land use change in the region. Spatial analysis tools in ArcGIS were employed to calculate proximity metrics and generate thematic layers.

2.5 Future Land Use Land Cover Prediction

The MOLUSCE module in QGIS was used to predict future LULC changes using a Cellular Automata and Neural Network (CA-ANN) model. This approach utilizes historical LULC maps for 2014, 2019 and 2024 as input layers, integrating spatial variables to simulate future scenarios. The projected maps offer insights into potential LULC dynamics based on observed trends.

Table 1: Area statistics of LULC classes for the years 2014, 2019 and 2024 and percentages of change.

LULC Classes	2014		2019		2024		Change in 2014-2019	Change in 2019-2024	Change in 2014-2024
	sq.km	%	sq.km	%	sq.km	%	Δ %	Δ %	Δ %
Water	0.04	0.00	0.33	0.02	0.08	0.01	0.02	-0.018	0.00
Trees	443.56	32.34	410.69	29.95	316.71	23.09	-2.40	-6.852	-9.25
Crop land	433.95	31.64	506.14	36.91	434.02	31.65	5.26	-5.259	0.00
Built areas	250.54	18.27	276.73	20.18	418.23	30.50	1.91	10.318	12.23
Rangeland	243.31	17.74	177.52	12.94	202.36	14.76	-4.80	1.812	-2.99

Table 2: Classification Accuracy Assessment of each Land use Maps.

LULC Classes	2014		2019		2024	
	Producer's Accuracy	User's Accuracy	Producer's Accuracy	User's Accuracy	Producer's Accuracy	User's Accuracy
Trees	0.97	1.00	0.97	1.00	0.96	0.77
Crop land	1.00	1.00	1.00	0.93	0.57	0.93
Built areas	0.96	1.00	0.92	1.00	0.79	0.54
Rangeland	1.00	0.86	1.00	1.00	0.90	0.69
Overall accuracy (%)	97.00		80.00		98.00	
Kappa coefficient	0.97		0.96		0.64	

3 RESULTS

3.1 Land Use Land Cover Classification

The LULC area statistics are shown in Table 1. The total surface area of the analysed area is 1,371.4028 km^2. The distribution of the Elgon LULC classes shows that in the year 2014, 32.34% of the area was forested, 31.64% cropland, 18.27% built-up, 17.74% rangeland and 0% water body. Whereas the year 2019 analysis shows that 36.91% of the Elgon region is agricultural land (cropland), 29.95% forest, 20.18% built-up, 12.94% pasture and 0.02% water body. In the year 2024, the agricultural, built-up, forest, rangeland and water bodies were 31.65, 30.50, 23.09, 14.76 and 0.01 percent respectively.

3.2 Classification Accuracy Assessment

The classification accuracy assessment (Table 2) for the LULC maps of 2014, 2019, and 2024 reveals a clear decline in both overall accuracy and class-specific reliability in 2024. While the Producer's and User's Accuracies for most land cover classes remained high in 2014 and 2019 with Overall Accuracy values of 97% and 98%, and Kappa Coefficients of 0.97 and 0.96, respectively, a substantial drop was observed in 2024. The Overall Accuracy fell to 80%, and the Kappa Coefficient dropped markedly to 0.64, indicating a notable decrease in agreement between the classified and reference data.

Class-specific performance in 2024 illustrates the nature of this decline. Built-up areas showed a pronounced reduction in both Producer's Accuracy (0.79) and User's Accuracy (0.54), implying increased confusion with other classes and potential overestimation of urban expansion. Cropland also exhibited a major drop in Producer's Accuracy from 1.00 (in 2014 and 2019) to 0.57 in 2024, indicating significant misclassification, even though its User's Accuracy remained stable at 0.93. Trees and rangeland, while more stable, also showed decreased User's Accuracy, suggesting reduced reliability in mapping these categories.

The reduced classification quality in 2024 may have compromised the accurate detection of land cover changes between 2019 and 2024. Misclassification of built-up or cropland areas could have resulted in either exaggerated or underestimated land transitions during this period.

Table 3: Change of area between LULC classes for the years 2014-2019, 2019-2024 and 2014-2024.

Changes between LULC classes	2014-2019 (sq.km)	2019-2024 (sq.km)	2014-2024 (sq.km)
Water to Water	1.00	0.22	0.86
Water to Trees	0.00	0.08	0.01
Water to Cropland	0.00	0.60	0.07
Water to Built-up areas	0.00	0.09	0.02
Water to Rangeland	0.00	0.02	0.04
Trees to Water	0.00	0.00	0.00
Trees to Trees	0.82	0.71	0.67
Trees to Cropland	0.05	0.05	0.07
Trees to Built-up areas	0.05	0.14	0.14
Trees to Rangeland	0.09	0.10	0.11
Cropland to Water	0.00	0.00	0.00
Cropland to Trees	0.03	0.01	0.02
Cropland to Cropland	0.86	0.75	0.74
Cropland to Built-up areas	0.06	0.16	0.19
Cropland to Rangeland	0.04	0.08	0.05
Built areas to Water	0.00	0.00	0.00
Built areas to Trees	0.05	0.00	0.00
Built areas to Cropland	0.08	0.03	0.05
Built areas to Built-up areas	0.86	0.96	0.94
Built areas to Rangeland	0.01	0.01	0.01
Rangeland to Water	0.00	0.00	0.00
Rangeland to Trees	0.09	0.10	0.04
Rangeland to Cropland	0.37	0.14	0.28
Rangeland to Built-up areas	0.06	0.10	0.15
Rangeland to Rangeland	0.48	0.66	0.5

Moreover, since future LULC projections up to 2054 are based on trends derived from historical and current maps, the 2024 dataset serves as a critical input. Lower classification confidence in this dataset may propagate uncertainty into the projection model, potentially distorting forecasts of land cover change particularly for rapidly evolving classes like urban or agricultural land.

3.3 Change of Area Between Land Use Land Cover Classes

When the change values are examined (Table 3); shrinkage was detected in water, trees, cropland, and rangeland by 0.02%, 9.25%, 5.26%, and 2.99 respectively with greater shrinkage in the trees (forested area) by 9.25% in the year 2014-2024, whereas expansion was observed in built-up areas throughout the years with greater expansion values by 12.23%, for the period 2014-2024.

The change analysis of the LULC classes showed that the expansion in the built-up areas had arisen from water bodies, Trees, Cropland and rangeland where 0.09, 0.14,0.19, and 0.15 Km^2 of respective LULC classes were transformed into built-up areas from the year 2014 to the year 2024. Over a 30-year period (2024-2054), the built-up area is projected to increase from 30.5 to 48.6 and the trees, croplands and rangelands to decrease from 23.1 to 14.4, 31.7 to 28.1 and 14.8 to 8.9 percent respectively, with minimal changes in water bodies.

3.4 Projected LULC Area Statistics for 2054 Relative to the Baseline (2014)

Figures 2 and 3 illustrate LULC changes between 2014 and 2024, along with projections for 2054. These figures highlight trends across various land cover categories, revealing a steady transformation of natural landscapes into urban and built-up areas.

A key trend is deforestation, with forest cover decreasing sharply from 32.34% in 2014 to a projected 14.40% by 2054. This persistent loss is driven by urban expansion, agricultural encroachment, illegal logging, and land degradation.

Urbanisation is another prominent trend, with built-up areas projected to nearly triple from 18.27% in 2014 to 48.55% by 2054. This surge is likely fueled by population growth, increased housing demand, infrastructure development, and rural-to-urban migration affecting green spaces and croplands, greater pollution, urban heat island effects, and heightened pressure on water and waste management systems.

Cropland initially increased between 2014 and 2019 due to agricultural expansion but is expected to decline from 2024 onward due to urban encroachment, soil degradation, and the impacts of climate change on agricultural productivity. The shrinking cropland base poses risks to food security and signals a shift in economic focus from agriculture toward industry and services.

Rangelands have also seen a significant decline from 17.74% in 2014 to a projected 8.91% in 2054. Contributing factors may include overgrazing, land degradation, urban encroachment, and climate change affecting pasture availability. This threatens livestock farming and may exacerbate soil degradation if unsustainable grazing continues.

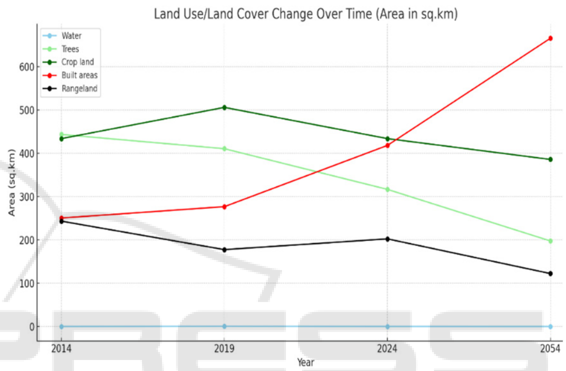

Figure 2: Visualizing Land Use Land Cover changes from 2014 to 2054.

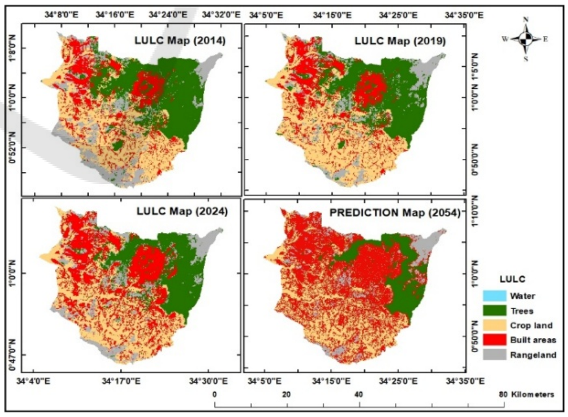

Figure 3: Spatial distribution of the LULC for the years 2014, 2019, 2024 and Prediction for 2054.

3.5 Association Between Driving Forces of Land Use Land Cover Change

Table 4 presents the explanatory power of each driver variable influencing LULC changes, measured using

Table 4: Cramer's V Values of Driver Variables.

Cramer's Coefficient		
Variable	**Cramer's V Value**	**Interpretation**
Population Growth	0.5316	Strong association
Distance from Rivers	0.3801	Moderate association
Distance from Roads	0.5337	Strong association
Slope	0.7205	Very strong association
DEM (Digital Elevation Model)	0.5236	Strong association
Hillshade	0.2973	Weak association
Aspect	0.4171	Moderate association

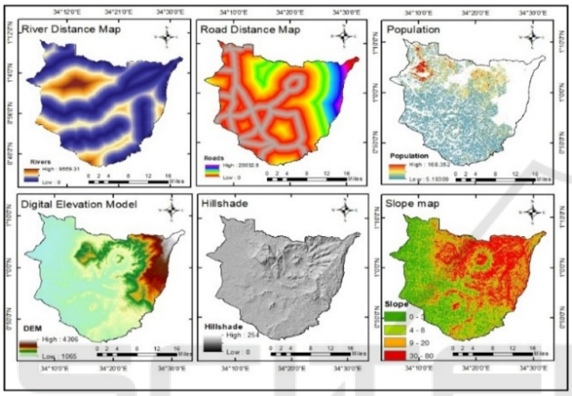

Figure 4: Distribution of driver variables.

the Cramer's V coefficient. All variables demonstrated significant associations, with Cramer's V values exceeding 0.15. Among them, distance from rivers (0.3801) and aspect (0.4171) exhibited moderate explanatory power. Hillshade showed a weaker association (0.2973), while population growth, distance to roads, elevation (DEM), and slope demonstrated strong correlations, slope showed a very strong relationship. Following the identification of these key drivers, the specified land cover transitions were modeled within a unified transition sub-model. This process produced transition potential maps, which demonstrated accuracy levels ranging between 40% and 95%.

4 DISCUSSION OF RESULTS

Land use and land cover change at global level is a problem for the environment and for development because of its complex nature and local occurrence. For the coming decades, the world population is expected to continue growing, causing major problems (Unger & Lakes, 2023). Land demand is reflected in different land-use interests, which can lead to land-use synergies that are manifested locally.

Satellite data allow continuous monitoring of land use change at various scales. It should also be noted that understanding the interrelationships between the various land use factors and their effects is conducive to optimising land use patterns and promoting land use sustainability. However, spatial differences and the drivers of synergies between the various land use factors in the region have not been well studied.

4.1 Historical Land Use Land Cover Change Dynamics Analysis

Historical changes in the LULC (Table 1) shows that agricultural land and rangelands have been reduced between 2014 and 2024. Trees have declined over the years, while built-up areas have increased steadily. Agricultural expansion (Alshari & Gawali, 2022) and urbanisation (Gündüz, 2025) has caused more than 28.6% of forest cover to be lost in the last 10 years. Similarly, studies in the region have reported that the conversion of forests and the reduction of rangelands are indicators of an increase in anthropogenic activity and food demand (Ojelabi et al., 2025). Historical findings on LULC dynamics align with studies showing that agricultural and urban expansion are driving the loss of natural vegetation (Alshari & Gawali, 2022).

4.2 Spatial and Temporal Land Use Change Trends

The analysis of Cramer's V values provided insights into the key drivers influencing LULC changes in the Mount Elgon region. These results are consistent with a study conducted in Sana'a City in Yemen (Ouma et al., 2024). Slope exhibited the strongest association (0.7205) (Xu et al., 2021).

Distance from roads (0.5337) and population growth (0.5316) also had strong associations, defining infrastructure development and urban expansion (Rahnama, 2021). DEM (0.5236) and distance from rivers (0.3801) influenced land use patterns (Abbas et al., 2021; Gharaibeh et al., 2020), while hillshade (0.2973) showed the weakest association (Ouma et al., 2024). These findings are consistent with the findings of Abijith et al. (2025) where DEM, slope and distance from roads including population growth contribute to the change in land use.

5 CONCLUSION AND FUTURE WORK

The study modeled LULC changes by analyzing key environmental and human-driven factors such as elevation, slope, distance from roads and rivers, and population growth. Accurate LULC modeling requires careful selection of relevant predictors and the use of spatiotemporal data to capture complex dynamics. Among the variables analyzed, slope showed the strongest influence, followed by distance to roads, elevation, and population growth. Distance to rivers and aspect had moderate associations, while hillshade had the weakest. Despite these insights, the study acknowledges limitations in simulating human behaviour and policy influences. To enhance predictive accuracy, future research should incorporate integrated models, scenario-based simulations, and advanced techniques like machine learning or Artificial Intelligence. Incorporating socio-economic drivers is also essential, as human activity significantly shapes LULC patterns.

DECLARATION OF COMPETING INTEREST

The authors declare that there were no known conflicting interests that could have influenced the work reported in this paper.

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