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Modeling Landcover and Landuse Change between 2000 and 2025 in Sapele LGA Using Artificial Neural Network

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Abstract
The landscape of Sapele LGA, is currently in the throes of transformative changes propelled by an amalgamation of factors, including rapid population growth, industrialization, and the ongoing expansion of urban areas. Despite the discernible evolution taking place, a noticeable void exists in our comprehensive understanding of the intricate spatio-temporal dynamics underpinning these urban development processes within Sapele LGA. Hence this study is aimed at a Spatio-temporal analysis of landcover/landuse dynamics in Sapele LGA, using gradient direction analysis and artificial neural network with the view of providing a framework for sustainable development. The objectives are to: investigate the spatial pattern of landcover/landuse in Sapele LGA over the last 25 years (2000 – 2025) using gradient direction analysis; ascertain the trend of the landcover/landuse dynamics over the last 25 years; determine the Landuse Intensity across Sapele LGA over the last 25 years. and predict the future landcover/landuse dynamics of Sapele LGA in 2040 using artificial neural network. A multi-temporal and multi-sensor approach was adopted to analyze landcover and landuse dynamics in Sapele Local Government Area between 2000 and 2025. Satellite imagery from Landsat 5, Landsat 7 ETM+, Landsat 8 OLI, and Sentinel-2 were used alongside ground control data for classification and accuracy validation. Supervised classification was conducted using the Random Forest algorithm in QGIS, while change detection, land use intensity analysis, and directional transition trends were assessed using post-classification comparison, gradient direction analysis, and land use intensity index computations. Future landcover prediction to the year 2050 was carried out using an Artificial Neural Network (ANN) model in the MOLUSCE plugin. The results revealed a significant increase in Built-Up Area from 18.78 km² in 2000 to 82.05 km² in 2025, while Open Space and Vegetation declined substantially. The Land Use Intensity Index rose from 1.334 in 2000 to 1.722 in 2025, indicating increasing anthropogenic pressure. Gradient direction analysis showed a consistent north-northeastward orientation of landcover change, aligning with urban expansion corridors. The ANN model predicted further transformation by 2050, projecting Built-Up Area to reach 123.62 km² and Open Space to reduce to less than 1 km². The findings of this study are recommended as a decision-support framework for guiding landcover and landuse management strategies within Sapele Local Government Area.

Keywords: Landcover, Landuse, Gradient Direction, Remote Sensing, Sapele LGA, Urban Dynamics, GIS, Land Use Intensity

1. Introduction
Landcover and landuse change (LULCC) has become one of the most critical indicators of anthropogenic impact on the environment, especially in rapidly urbanizing regions across the Global South.

These changes not only reflect shifts in socio-economic and political processes but also represent fundamental transformations of the Earth's surface with far-reaching consequences for ecological integrity, climate regulation, and sustainable development (Lambin *et al*., 2003; Foley *et al*., 2005) [6, 4]. The dynamic interaction between human settlements, agricultural expansion, deforestation, and infrastructural development contributes significantly to land transformation patterns observed globally (Turner *et al*., 2007) [12].

In Nigeria, landcover change has accelerated significantly over the past two decades, fueled by population growth, industrialization, and weak enforcement of land use policies (Ndukwu & Achi, 2018) [8]. Sapele Local Government Area (LGA) in Delta State serves as a microcosm of these broader transformations, with its rapidly changing landscape influenced by urban expansion, timber processing, oil-related activities, and agricultural encroachment. The area's unique location in the Niger Delta, coupled with its industrial significance, makes it particularly susceptible to landcover transitions that can compromise ecosystem services, reduce biodiversity, and intensify flood vulnerability (Abua & Ekpo, 2015; Dike *et al*., 2018) [1, 3].

Detecting, quantifying, and modeling these changes is essential for effective land management, spatial planning, and environmental monitoring. Traditional techniques of change detection, such as pixel-based classification and image differencing, while useful, often fail to adequately model the complex, non-linear patterns of land transformation over time (Singh, 1989) [10]. As such, the adoption of Artificial Neural Networks (ANNs) for LULC modeling has gained traction due to their ability to learn from historical transitions, integrate multiple driving factors, and simulate future scenarios with high spatial and temporal resolution (Al-sharif & Pradhan, 2014; Tayyebi *et al*., 2011) [2, 11].

ANNs, inspired by the structure of biological neurons, are well-suited for landuse modeling because they can model spatial processes that are both stochastic and deterministic in nature (Pijanowski *et al*., 2002) [9]. By training the network with historical landcover data and relevant driving factors—such as elevation, proximity to roads, and existing urban zones—ANNs can predict the probability of transition from one landcover class to another (Li & Yeh, 2002) [7]. This capability has proven valuable for land managers and urban planners seeking to anticipate urban sprawl, manage agricultural resources, and conserve sensitive ecosystems.

In the context of Sapele LGA, there is a growing need for predictive modeling that captures not only the historical evolution of landuse but also forecasts its future state under a "business-as-usual" scenario. The integration of remote sensing data from platforms such as Landsat and Sentinel with machine learning models like ANN provides an efficient, scalable, and reproducible approach for such modeling (Guan *et al*., 2011) [5]. This study thus aims to develop an ANN-based model to analyze historical landcover change in Sapele LGA between 2000 and 2025 and to simulate its possible configuration by 2050. Understanding these trends is essential not only for academic purposes but also for policy formulation, disaster risk reduction, and environmental impact assessment in an increasingly urbanized and ecologically fragile region. By deploying intelligent modeling techniques, this research contributes to the growing body of knowledge on spatial transformation and offers a decision-support tool for sustainable land governance.

2. Materials and Methods

2.1 Study Area Description

The study was conducted in Sapele Local Government Area (LGA), situated in the southwestern part of Delta State, Nigeria. Geographically, Sapele LGA lies within latitudes 5°50′N to 5°59′N and longitudes 5°40′E to 5°52′E. The area covers an approximate landmass of 580 square kilometers and is characterized by a tropical rainforest climate with two distinct seasons—rainy and dry. The mean annual rainfall exceeds 2,500 mm, while the average temperature hovers around 27°C. Topographically, the region is relatively flat, with low-lying plains that make it susceptible to flooding and land use conflicts. Its strategic location along the Benin River and its proximity to Warri port and industrial hubs make it a significant center of economic and industrial activities in Delta State. These anthropogenic pressures have influenced the transformation of landcover and landuse over time.

2.2 Data Sources and Satellite Imagery

To assess the spatio-temporal dynamics of landcover/landuse (LULC) in Sapele LGA, a multi-temporal and multi-sensor approach was adopted. Satellite images used in this study include Landsat 5 Thematic Mapper (TM) for the year 2000 and Landsat 7 Enhanced Thematic Mapper Plus (ETM+) for the year 2005. These images were selected due to their spatial resolution of 30 meters and the consistency of the temporal coverage over the study period. All images were acquired from the United States Geological Survey (USGS) EarthExplorer portal, which provides pre-processed Level-1 terrain-corrected products. Only images with minimal cloud cover (<10%) and acquired within the same season (preferably dry season) were selected to ensure comparability.

2.3 Image Preprocessing

Image preprocessing is essential to enhance image quality and improve classification accuracy. The Landsat images were subjected to both radiometric and atmospheric corrections using the Semi-Automatic Classification Plugin (SCP) in QGIS 3.28. Radiometric correction was carried out to convert digital numbers (DN) into top-of-atmosphere reflectance values, thereby minimizing the influence of sensor calibration errors. Atmospheric correction was applied using the Dark Object Subtraction (DOS) method to remove haze and scattering effects. The images were also clipped to the Sapele LGA boundary using the administrative shapefile obtained from the Office of the Surveyor General of the Federation (OSGOF).

2.4 Training Sample Collection and Classification

Landcover/landuse classification was performed using a supervised classification method. Training samples representing five major classes—Built-up Area, Vegetation, Waterbody, Open Land, and Wetland—were generated based on field observations, historical land records, and high-resolution reference data from Google Earth. These samples were used to train a machine learning classifier using the Random Forest algorithm, which has been proven to provide high classification accuracy and robustness to noisy data. The classification was conducted within the SCP environment in QGIS, with 70% of the samples used for training and 30% reserved for accuracy assessment.

2.5 Accuracy Assessment
After classification, accuracy assessment was conducted using a confusion matrix generated by comparing the classified results with independent validation data. Overall accuracy, producer's accuracy, user's accuracy, and the kappa coefficient were calculated. The overall accuracy for 2000 and 2005 images were 88.3% and 91.2%, respectively, with kappa coefficients exceeding 0.80, indicating strong agreement between classified maps and reference data.

2.6 Change Detection Analysis
Post-classification comparison was used to evaluate landcover/landuse changes between 2000 and 2005. This method involves overlaying classified images from two time periods to generate a change matrix, which quantifies gains and losses in each LULC category. The analysis enabled the detection of specific transitions, such as vegetation-to-built-up or wetland-to-open land, which are critical in understanding the magnitude and direction of land transformation.
To further evaluate human-induced change, the Land Use Intensity Index (LUI) was calculated using the formula:

$$\text{LUI} = \frac{\text{Number of changed pixels}}{\text{Total number of pixels}} \times 100$$

The index measures the proportion of land experiencing transitions within the study period, thereby reflecting the degree of anthropogenic pressure on the landscape.

2.7 Gradient Direction Analysis
To determine the spatial orientation and pattern of landcover/landuse transitions, gradient direction analysis was carried out. This analysis used centroid displacement and vector analysis techniques to trace the movement of land use changes from 2000 to 2005. Specifically, the spatial centroid of each landcover class was calculated for both years, and the vector displacement between centroids was used to determine the direction and magnitude of change. The resulting vectors were classified into eight directional zones: North, Northeast, East, Southeast, South, Southwest, West, and Northwest. The dominant direction of expansion was identified and visualized using rose diagrams and vector field overlays in QGIS.
Gradient direction analysis is particularly useful in identifying urban sprawl corridors and environmental stress zones, especially in rapidly urbanizing regions like Sapele LGA. This method allowed the study to uncover whether land development was biased toward industrial corridors, riverine areas, or transportation nodes.

2.8 Artificial Neural Network (ANN) Simulation
In order to forecast future landcover and landuse (LULC) conditions in Sapele Local Government Area, an Artificial Neural Network (ANN)-based simulation was carried out using the MOLUSCE (Modules for Land Use Change Evaluation) plugin integrated within QGIS 3.28. The aim of this simulation was to generate a predictive landcover map for the year 2050 by leveraging observed historical landcover transitions from the years 2000 through 2025. The ANN model was chosen due to its proven ability to capture complex non-linear relationships among spatial variables and to learn generalized transition patterns from temporal data without relying on rigid statistical assumptions.
The input data used for the ANN model included a series of classified landcover maps for the years 2000, 2005, 2010, 2015, 2020, and 2025. Additionally, change detection layers were generated to represent the transition probabilities between LULC classes. These layers were complemented by explanatory driving variables, which were derived from spatial analysis and included factors such as elevation data from the Shuttle Radar Topography Mission (SRTM), distance to roads, proximity to water bodies, and the spatial proximity to existing built-up areas. All raster datasets were projected to a common spatial reference system (WGS 84 / UTM Zone 31N) and resampled to ensure consistent resolution across layers.
Training of the ANN model was conducted using the Multi-Layer Perceptron (MLP) architecture, where the network learns by adjusting connection weights through backpropagation. A portion of the available dataset (70%) was used for training, while the remaining 30% was set aside for model validation. The ANN model iteratively minimized the prediction error between observed and predicted LULC transitions, allowing it to identify spatial rules associated with land changes, such as vegetation loss to urban expansion and conversion of open lands to built-up zones.
Once the model was adequately trained, it was used to simulate the landcover configuration for the year 2050. This simulation followed a "business-as-usual" scenario, assuming that current trends in land transformation would continue without any significant policy intervention. The result was a classified raster map representing the predicted spatial distribution of landcover classes in 2050, as well as a transition probability surface showing the likelihood of individual pixels undergoing specific class changes.
The ANN simulation revealed areas with high probability of urban encroachment, projected expansion corridors, and zones where natural vegetation may potentially recover due to reduced development intensity. These spatially explicit projections are instrumental for decision-makers in urban planning, environmental management, and infrastructure development. They offer valuable insight into future land consumption patterns, inform sustainable land allocation, and assist in identifying ecologically sensitive areas that may require conservation efforts. The use of ANN modeling within this context demonstrates the utility of intelligent predictive tools in supporting forward-looking spatial planning and environmental stewardship.

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3. Results
3.1 Landcover/Landuse Class Distribution (2000–2025)
An assessment of the landcover/landuse statistics across the study period further highlighted the profound transformations that occurred between 2000 and 2025. The landcover classes considered include Built-Up Area, Vegetation, Open Space, and Wetland.
In the year 2000, Open Space was the most dominant landcover class, covering approximately 371.503 km² or 82.47% of the total area. Vegetation accounted for 26.327 km² (5.84%), Wetlands covered 33.824 km² (7.51%), while Built-Up Areas were relatively limited, covering only 18.780 km² (4.17%), see table 1 and figure 1.

Table 1: Landcover/landuse Distribution for Sapele LGA in 2000

S/N	Class (Year 2000)	Area (Km^2)	Percentage
1	Built Up Area	18.780	4.17
2	Vegetation	26.327	5.84
3	Open Space	371.503	82.47
4	Wetland	33.824	7.51

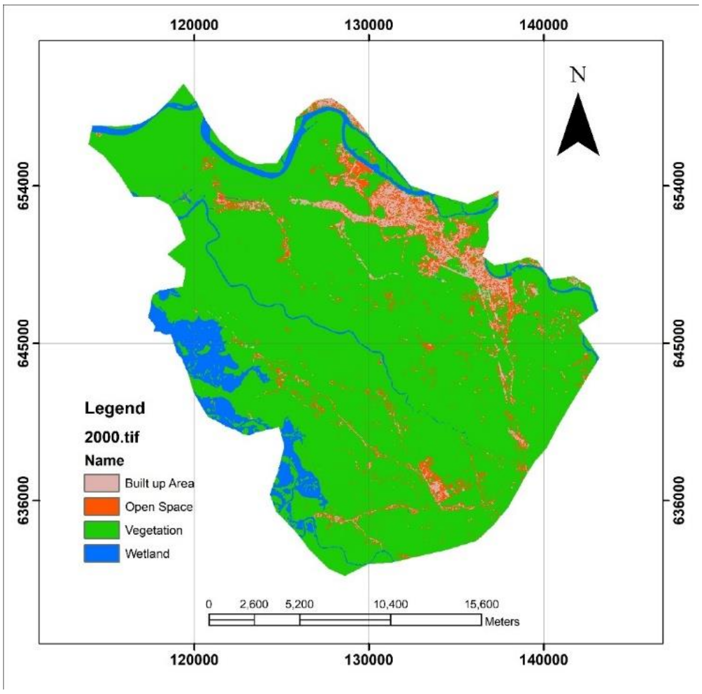

Fig 1: Landcover/landuse Map of Sapele 2000

By 2005, there was a notable expansion in Built-Up Area, which increased to 29.924 km² (6.64%), while Vegetation expanded significantly to 68.328 km² (15.17%). However, Open Space decreased to 323.050 km² (71.72%), indicating land consumption for built-up purposes. Wetland areas slightly reduced to 29.132 km² (6.47%), see table 2 and 2.

Table 2: Landcover/landuse Distribution for Sapele LGA in 2005

S/N	Class (Year 2005)	Area (Km^2)	Percentage
1	Built Up Area	29.924	6.64
2	Vegetation	68.328	15.17
3	Open Space	323.050	71.72
4	Wetland	29.132	6.47

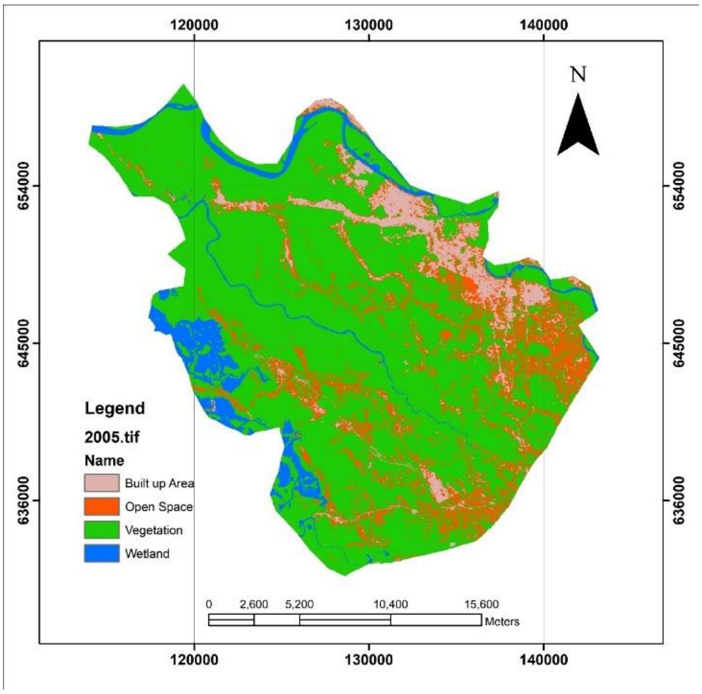

Fig 2: Landcover/landuse Map of Sapele 2005

The trend continued into 2010, with Built-Up Area increasing further to 41.513 km² (9.22%), while Vegetation dramatically decreased to 27.004 km² (5.99%). Open Space slightly rebounded to 337.731 km² (74.97%), possibly due to reclassification or temporal land abandonment, while Wetland coverage rose to 44.183 km² (9.80%), indicating localized wetland expansions, see table 3 and figure 3.

Table 3: Landcover/landuse Distribution for Sapele LGA in 2010

S/N	Class (Year 2010)	Area (Km^2)	Percentage
1	Built Up Area	41.513	9.22
2	Vegetation	27.004	5.99
3	Open Space	337.731	74.97
4	Wetland	44.183	9.80

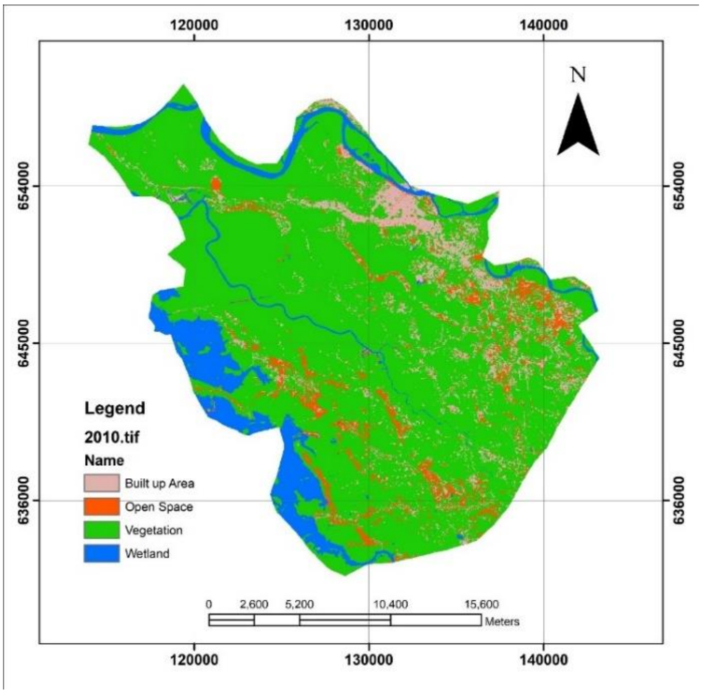

Fig 3: Landcover/landuse Map of Sapele 2005

In 2015, Built-Up Area slightly increased to 43.470 km² (9.65%), while Vegetation continued its downward trend, reducing to 15.726 km² (3.49%). Open Space expanded to 352.029 km² (78.15%), while Wetland areas declined marginally to 39.211 km² (8.70%), see table 4 and figure 4.

Table 4: Landcover/landuse Distribution for Sapele LGA in 2015

S/N	Class (Year 2015)	Area (Km^2)	Percentage
1	Built Up Area	43.470	9.65
2	Vegetation	15.726	3.49
3	Open Space	352.029	78.15
4	Wetland	39.211	8.70

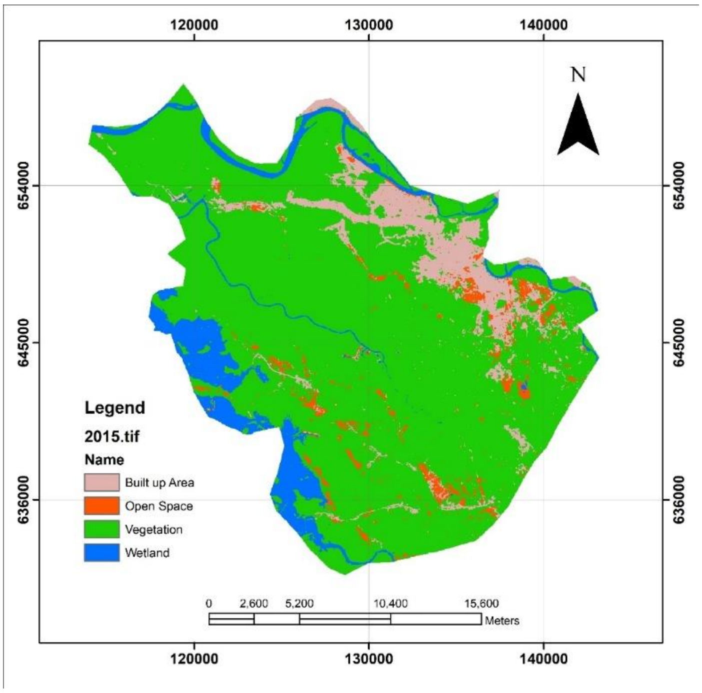

Fig 4: Landcover/landuse Map of Sapele 2015

By 2020, Built-Up Areas experienced substantial growth, reaching 58.726 km² (13.04%), reflecting intensified urbanization. Vegetation decreased further to 13.772 km² (3.06%), while Open Space contracted to 335.245 km² (74.43%), and Wetland slightly expanded to 42.675 km² (9.47%). See table 5 and figure 5.

Table 5: Landcover/landuse Distribution for Sapele LGA in 2020

S/N	Class (Year 2020)	Area (Km^2)	Percentage
1	Built Up Area	58.726	13.04
2	Vegetation	13.772	3.06
3	Open Space	335.245	74.43
4	Wetland	42.675	9.47

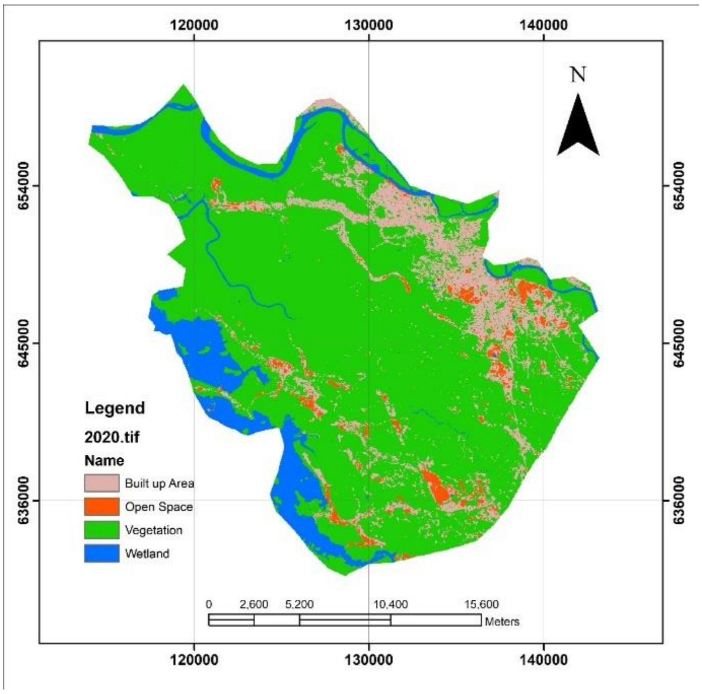

Fig 5: Landcover/landuse Map of Sapele 2020

In 2025, Built-Up Area occupied approximately 82.046 km² (18.21%), signifying a near five-fold increase from the baseline year 2000. Vegetation remained critically low at 13.382 km² (2.97%), highlighting significant landscape alteration. Open Space decreased further to 322.079 km² (71.49%), while Wetland areas declined to 32.971 km² (7.32%), see table 4.6, figure 6 and 7.

Table 6: Landcover/landuse Distribution for Sapele LGA in 2025

S/N	Class (Year 2025)	Area (Km^2)	Percentage
1	Built Up Area	82.046	18.21
2	Vegetation	13.382	2.97
3	Open Space	322.079	71.49
4	Wetland	32.971	7.32

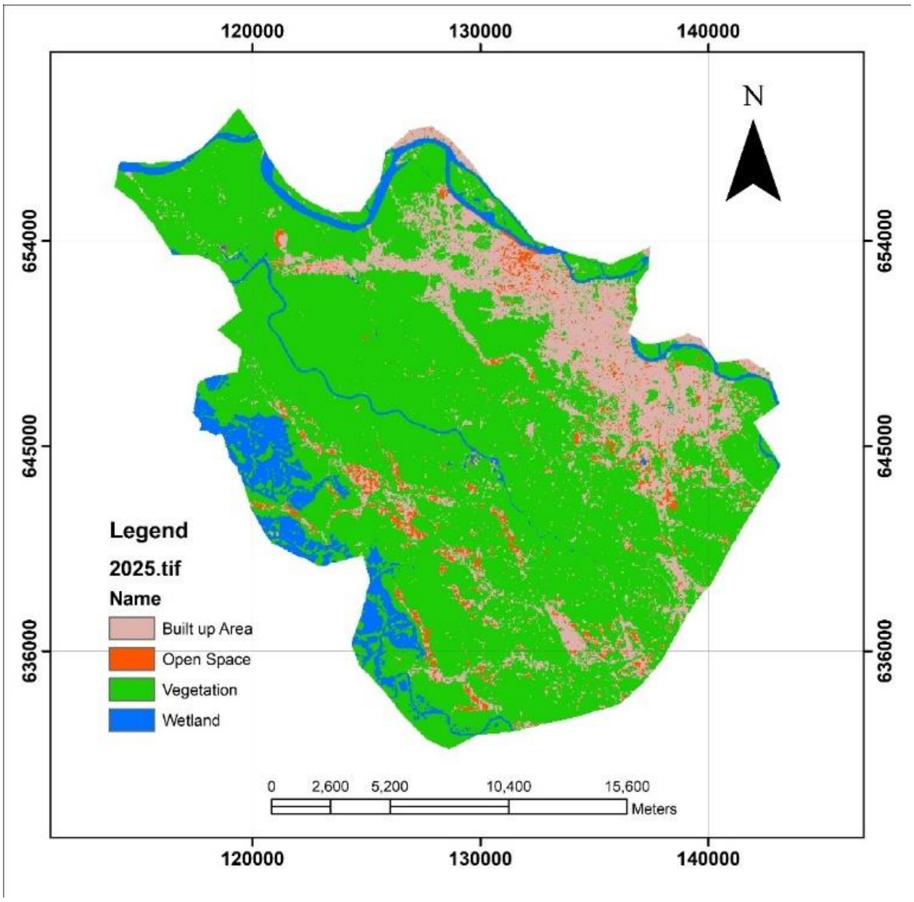

Fig 6: Landcover/landuse Map of Sapele 2025

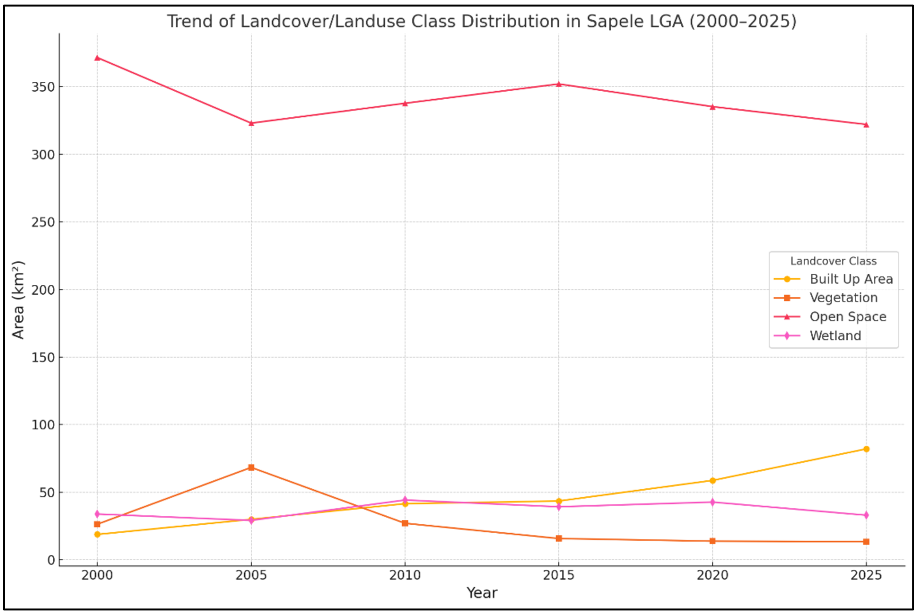

Fig 7: Trend of Landcover/Landuse Distribution in Sapele LGA (2000 -2025)

3.2 Spatial Pattern of Landcover/Landuse Dynamics (2000–2025) Based on Gradient Direction Analysis

The spatial analysis of landcover/landuse dynamics in Sapele LGA between 2000 and 2025 was undertaken using Gradient Direction Analysis. This approach provided valuable insight into the intensity and directional trends of landcover transitions over the 25-year period, see figure 8.

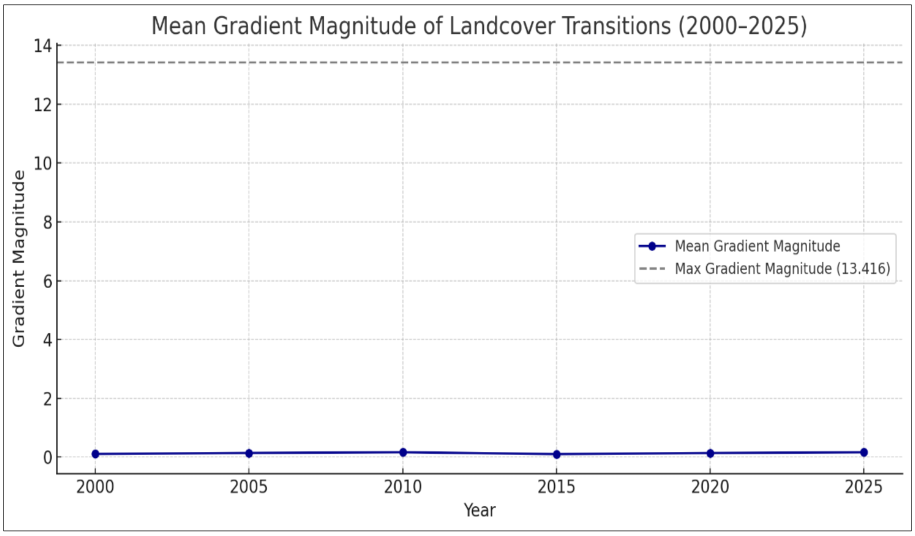

Fig 8: Mean Gradient Magnitude of Landcover Transitions in Sapele LGA (2000 -2025)

The Mean Gradient Magnitude, which represents the spatial intensity of landcover transitions, exhibited a dynamic trend over the study period. In 2000, the mean gradient magnitude was recorded at 0.108, indicating moderate spatial changes primarily associated with natural landcover types. A noticeable increase occurred in 2005, with the mean magnitude rising to 0.141, indicating intensification of landcover transitions, likely linked to the onset of urbanization activities. This trend continued into 2010, where the mean magnitude peaked at 0.165, implying a period of rapid urban expansion and landscape transformation.

However, by 2015, a temporary decline was observed, with the mean magnitude decreasing to 0.103, indicating a brief slowdown or stabilization in spatial transitions. This deceleration was short-lived, as 2020 experienced a resurgence in landcover changes, with the mean gradient magnitude rising again to 0.139, and further increasing to 0.164 by 2025, reaffirming the ongoing intensification of urban and infrastructural developments.

Throughout the period, the Maximum Gradient Magnitude remained consistently high at 13.416, across all years analyzed. This consistency indicated the presence of localized areas undergoing intense landcover changes, potentially corresponding to newly developing urban fringes and zones of active wetland modification.

Analysis of the Mean Gradient Direction (figure 9), revealed a consistent north-north-eastward orientation of landcover transitions across all years. In 2000, the mean direction was approximately 14.85°, which shifted slightly to 24.17° by 2005. A moderate adjustment occurred in 2010, with the mean direction at 21.63°, followed by a more northward orientation of 11.54° in 2015. By 2020, the mean direction had settled at 15.99°, and slightly adjusted to 19.71° by 2025. These findings confirm that the dominant spatial progression of landcover transitions, particularly urbanization, was consistently oriented towards the North-Northeast quadrant of the study area.

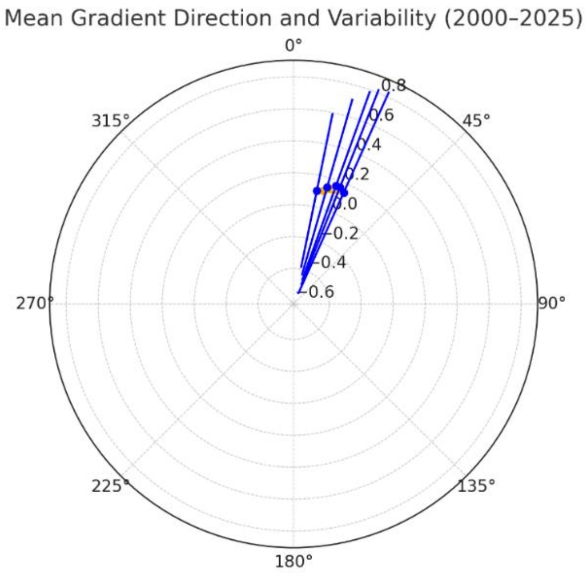

Fig 9: Mean Gradient Direction and Variability of Landcover Transitions in Sapele LGA (2000 -2025)

Furthermore, the Standard Deviation of Gradient Direction, which represents the variability of transition directions, fluctuated during the study period. A relatively higher variability was recorded in 2005 (69.31°) and 2010 (65.89°), indicating spatial changes occurring in multiple directions. This variability reduced to 49.40° by 2015, indicating a more focused and organized land development trend. However, moderate increases in variability were observed again in 2020 (57.46°) and 2025 (62.96°), indicating the emergence of new transition directions possibly associated with expanded urban and infrastructural activities in newly developing areas.

In general, the Gradient Direction Analysis demonstrates that landcover transitions in Sapele LGA were neither random nor isotropic but exhibited a consistent spatial progression towards the North-Northeast, with increasing intensity over time. This pattern reflects the combined effects of urban expansion, infrastructural developments, and associated land transformation processes within the LGA.

3.3 Change Detection Between 2000 and 2025

The landcover and landuse pattern in Sapele Local Government Area between 2000 and 2025 underwent significant transformations across the major classes: Built-Up Area, Vegetation, Open Space, and Wetland (figure 10).

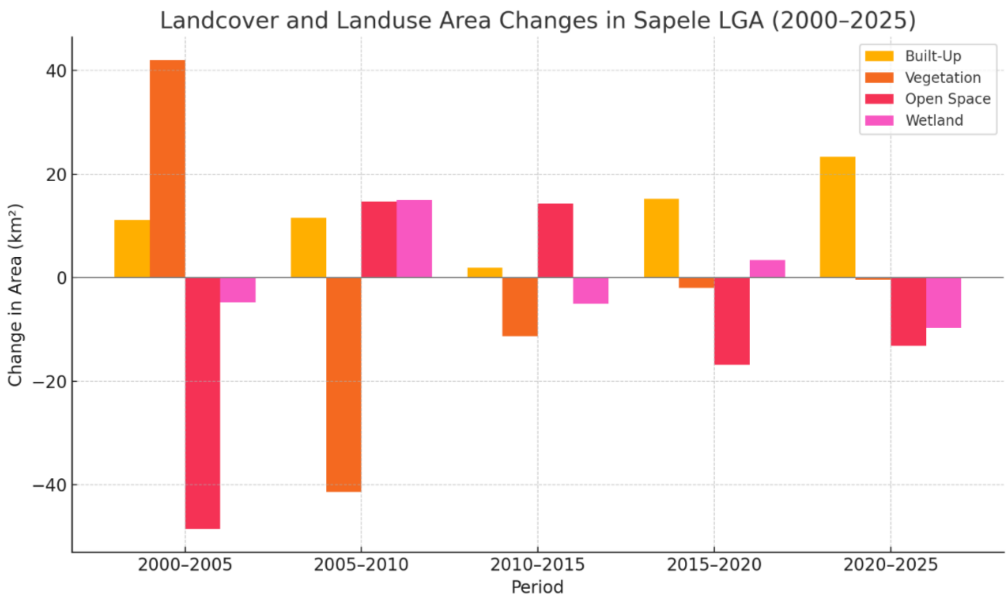

Fig 10: Landcover/Landuse Area Changes in Sapele LGA (2000 -2025)

Between 2000 and 2005, Built-Up Areas experienced a substantial increase of 11.144 km², indicating a strong onset of urbanization. Vegetation also recorded an exceptional gain of 42.001 km² within the same period, which may be attributed to reforestation efforts, classification adjustments, or temporary land-use recovery. Meanwhile, Open Space declined by 48.453 km², marking a major loss of undeveloped land, while Wetland areas reduced by 4.692 km², pointing to the early stages of wetland degradation. During the period 2005 to 2010, the Built-Up Area continued to expand, gaining 11.589 km². However, Vegetation suffered a sharp decline, losing 41.324 km². This significant vegetation loss points to widespread deforestation and land clearing activities linked to urban growth and agricultural expansion. Conversely, Open Space slightly increased by 14.681 km², and Wetlands expanded markedly by 15.051 km², indicating hydrological restoration or improved wetland delineation.

The landcover changes from 2010 to 2015 showed a relative slowdown in urban expansion, with Built-Up Areas increasing by only 1.957 km². Vegetation continued its downward trend, declining by 11.278 km², while Open Space increased by 14.298 km², possibly as a result of abandoned or cleared land not yet developed. Wetland areas, however, experienced a modest loss of 4.972 km². Between 2015 and 2020, urban development regained momentum as Built-Up Areas expanded significantly by 15.256 km². Vegetation loss persisted, albeit at a slower rate, with a reduction of 1.954 km². Open Space decreased by 16.784 km², signaling intensifying land pressures, while Wetlands exhibited a slight gain of 3.464 km², indicating localized restoration efforts or seasonal wetland dynamics.

Finally, from 2020 to 2025, Built-Up Areas experienced their highest expansion over the entire study period, with an increase of 23.320 km². Vegetation loss slowed substantially, recording a marginal decline of 0.390 km². Open Space reduced further by 13.166 km², while Wetlands suffered a substantial decrease of 9.704 km², reinforcing concerns over wetland vulnerability in the face of expanding urbanization. Overall, the period from 2000 to 2025 highlights a clear trend of urban expansion, steady vegetation depletion, gradual open space reduction, and unstable wetland dynamics across Sapele LGA.

3.4 Trend and Annual Rate of Landcover Change within Sapele LGA between 2000 and 2025

The analysis of the rate of landcover change between 2000 and 2025 reveals varied dynamics across different periods, reflecting fluctuating landuse pressures and environmental responses (figure 11).

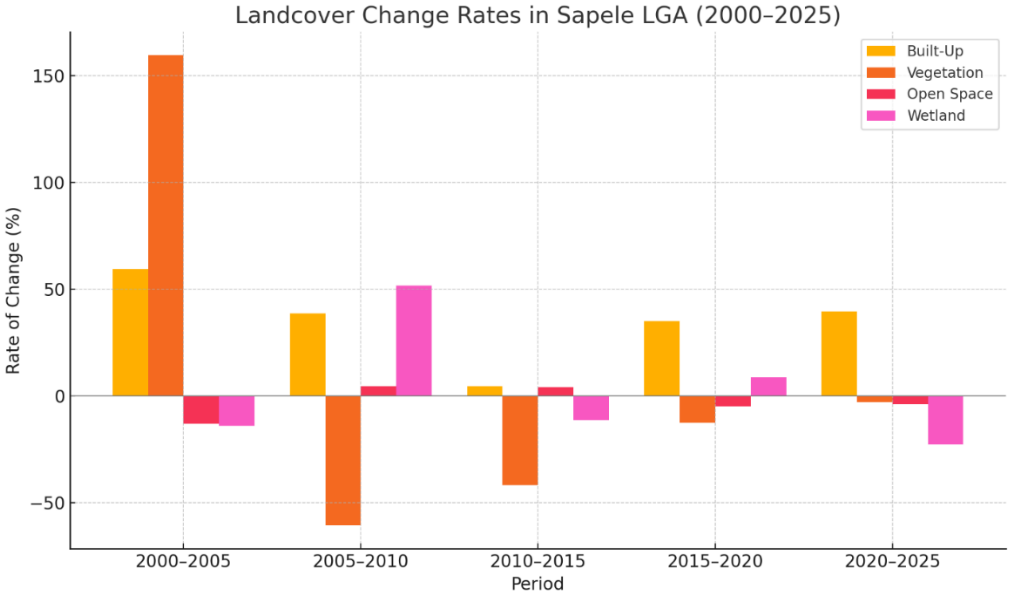

Fig 11: Landcover/Landuse Changes Rates in Sapele LGA (2000 -2025)

From 2000 to 2005, the Built-Up Area grew by 59.34%, at an annual rate of 11.87%, signaling an early rapid phase of urban expansion. During the same period, Vegetation increased remarkably by 159.54% (an annual rate of 31.91%), while Open Space declined moderately by -13.04% (annual rate of -2.61%) and Wetland reduced by -13.87% (annual rate of -2.77%). Between 2005 and 2010, urban expansion continued, with Built-Up Areas growing by 38.73% (annual 7.75%). However, this period witnessed a drastic loss of Vegetation, which declined by -60.48% at an alarming annual rate of -12.10%. Open Space slightly increased by 4.54%, while Wetland areas recovered impressively, growing by 51.66% (annual 10.33%).

During 2010 to 2015, the rate of Built-Up Area growth slowed significantly to 4.71% (annual rate 0.94%), indicating a temporary stabilization. Vegetation continued its sharp decline, reducing by -41.76% (annual rate -8.35%), while Open Space experienced a modest rise of 4.23%. Wetlands, however, declined by -11.25%, indicating environmental stress. The period 2015 to 2020 marked a renewed surge in urbanization, with Built-Up Areas increasing by 35.10% (annual 7.02%). Vegetation loss slowed to -12.43% (annual -2.49%), and Open Space reduced slightly by -4.77%. Wetland areas grew by 8.83%, indicating some positive hydrological conditions or management interventions. Finally, from 2020 to 2025, Built-Up Areas recorded a strong expansion rate of 39.71% (annual 7.94%), whereas Vegetation showed a minimal loss of -2.83% (annual -0.57%), indicating a nearing saturation of buildable land. Open Space declined by -3.93%, while Wetlands suffered a significant reduction of -22.74% (annual -4.55%), highlighting continued environmental vulnerability.

In summary, the period from 2000 to 2025 in Sapele LGA has been characterized by consistent Built-Up Area expansion, fluctuating Vegetation dynamics, progressive loss of Open Space, and episodic but overall declining Wetland coverage, with varying rates across different intervals.

3.5 Land Use Intensity Index (LUI) Analysis (2000–2025)

The Land Use Intensity Index (LUI) provides a comprehensive indicator for evaluating the degree to which land is utilized based on the anthropogenic pressure associated with various landcover classes. This index is particularly useful in tracking the transformation of natural landscapes into built environments, thereby offering a lens through which spatial planners and environmental analysts can assess developmental dynamics. For this study, weights were assigned to landcover categories based on their assumed intensity of use: Built-Up Areas (4), Wetland (3), Vegetation (2), and Open Space (1). These weights reflect the degree of environmental alteration and human influence associated with each category, where higher weights indicate more intense use (figure 12).

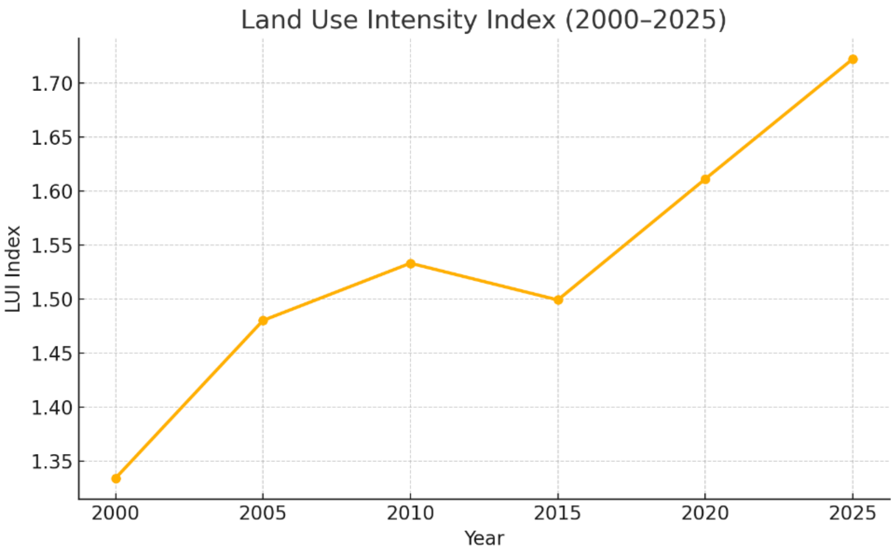

Fig 12: Landcover/Landuse Intensity Index (2000 -2025)

In the year 2000, Sapele LGA exhibited a relatively low land use intensity, with an LUI value of 1.334. At this time, the landscape was dominated by Open Space, accounting for over 80% of the area, while Built-Up Areas occupied only a small fraction. This configuration signified a largely undeveloped terrain with extensive ecological coverage, minimal urban encroachment, and relatively low environmental stress. The low LUI at this point in time indicated a landscape that still retained its natural buffering capacity and biodiversity functions.

By 2005, the LUI had increased to 1.480, reflecting the early stages of intensifying land use. This shift was driven largely by a noticeable increase in Built-Up Areas and a surge in vegetative cover, the latter possibly due to improved classification or actual landscape regeneration. The increase in land use intensity indicated the commencement of urban expansion, infrastructure development, and possibly agricultural activities. Though the ecological balance was not yet critically affected, the upward trend in LUI indicated that human-induced changes were beginning to take root more aggressively.

In 2010, the LUI continued its ascent to 1.533, fueled by continued growth in urban areas and a corresponding decline in vegetation. Wetlands, however, experienced an unexpected increase, which may have resulted from seasonal hydrological shifts or improved remote sensing detection. Despite the fluctuating ecological categories, the persistence of upward pressure on Built-Up Area expansion marked a steady shift towards a more anthropogenically influenced landscape. This period represented a transition phase where development began to encroach more visibly on vegetated and open spaces.

The year 2015 showed a slight moderation in LUI growth, reaching 1.499. While Built-Up Areas continued to increase, the pace slowed marginally, possibly due to temporary stagnation in urban infrastructure projects or localized land policy interventions. Vegetation continued to decline, as did Wetlands, indicating a reduction in the ecological resilience of the region. The persistence of high intensity despite slower development points to a scenario where cumulative effects of land transformation outweighed the gains from any environmental preservation measures.

In 2020, the LUI index rose sharply to 1.611, highlighting a new wave of intensified land use driven predominantly by an accelerated expansion of Built-Up Areas. By this point, built infrastructure had consumed a significantly larger proportion of land, while Vegetation reached one of its lowest levels across the study period. This rapid transformation underscores increasing population pressure, urban sprawl, and weak regulatory enforcement in managing land consumption. The implication here is a substantial loss of ecosystem services, increased flood risk, and degradation of environmental quality, especially in areas historically protected by vegetation buffers and natural drainage corridors.

By 2025, the LUI reached a peak of 1.722, the highest recorded across the entire 25-year observation period. Built-Up Areas had increased more than fourfold compared to the year 2000, a clear testament to aggressive urbanization and the growing demand for residential, industrial, and commercial land. Meanwhile, Vegetation and Wetlands continued their downward trends, resulting in a highly modified landscape dominated by impervious surfaces and reduced ecological functions. This level of land use intensity implies not only environmental degradation but also social and economic consequences, such as reduced agricultural productivity, water scarcity, and heightened vulnerability to climate-induced hazards.

The steady rise in the LUI from 2000 to 2025 reflects a transition from a predominantly natural landscape to one increasingly shaped by human needs. It emphasizes the necessity for integrated spatial planning, with a focus on balancing urban growth with environmental conservation. If unchecked, the current trajectory portends a future where ecological thresholds may be surpassed, thereby undermining the long-term sustainability of the region.

3.6 Landscape Prediction to 2040

The prediction of landcover dynamics for Sapele Local Government Area (LGA) using data between 2000 and 2025 was enhanced using an Artificial Neural Network (ANN) model implemented via the MOLUSCE plugin in QGIS. This data-driven modeling approach was chosen for its ability to learn complex, non-linear spatial patterns in landcover change from historical data. The ANN was configured with a neighborhood size of 1 pixel, corresponding to a 3x3 spatial window. This setting allowed the model to evaluate local spatial dependencies and interactions in land transformation. The learning rate was set at 0.100, providing a balance between convergence speed and model stability. The network architecture included 10 hidden neurons, which enabled it to capture intermediate relationships between inputs and outputs during training. Training was carried out over a maximum of 1000 iterations. To improve convergence and reduce oscillations during training, a momentum value of 0.050 was applied. The performance of the network was evaluated through internal metrics, which showed a slight decline in overall accuracy (−0.00778), indicating minor fluctuations between training and validation performance. However, this change did not significantly impact the model's predictive reliability.

Most importantly, the ANN achieved a minimum validation error of 0.02503 and a validation Kappa coefficient of 0.8593. The Kappa value, which measures agreement between predicted and actual class changes beyond chance, falls within the range generally considered "very good" in spatial modeling. This high validation Kappa reinforces the reliability of the ANN in capturing realistic transition potentials and underlying spatial dynamics of landcover change in the study area (figure 13).

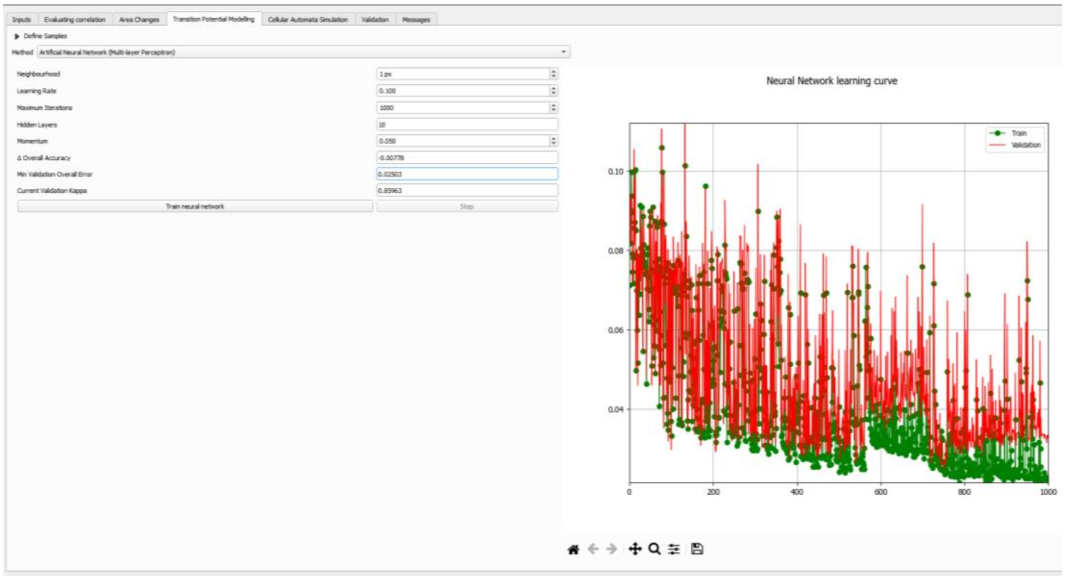

Fig 13: Artificial Neural Network Model Training

3.6.1 Transition Potential Matrix

The resulting transition potential matrix, derived from the ANN model, quantifies the likelihood of each landcover class in 2025 being derived from each class in 2000. The rows of the matrix represent the current (initial) landcover classes, while the columns represent the potential future classes. Each value ranges from 0 to 1, with higher values indicating stronger transition tendencies or class stability.

Built-Up Areas show a high degree of persistence, with a self-transition value of 0.8095. This indicated that once developed, urban areas are highly stable and unlikely to revert to other landcover types. However, there are still modest probabilities of Built-Up Areas transitioning to Open Space (0.1024) and Vegetation (0.0864). These transitions could reflect urban decline, underutilized developments, or classification ambiguities. The transition potential to Wetland (0.0017) is extremely low, indicating clear spatial separation between urban and wetland zones, possibly due to environmental restrictions or hydrological constraints.

Open Space, on the other hand, exhibits a high tendency to transition into Built-Up Areas, with a probability of 0.6500. This highlights the role of Open Space as a primary source for urban expansion in Sapele LGA. The probability of transitioning to Vegetation is 0.2659, indicating some degree of natural regeneration or temporary land abandonment. The self-transition value for Open Space is relatively low at 0.0812, indicating that Open Space is a transitional or temporary class, vulnerable to change. Very limited transitions to Wetlands (0.0030) were recorded, reinforcing its distinct ecological character.

Vegetation displays a strong level of persistence, with a self-transition probability of 0.8312, meaning that most vegetated areas are likely to remain unchanged. However, it is still susceptible to urban pressure, as indicated by a 13.4% probability of converting to Built-Up Area. This reflects ongoing deforestation and conversion of vegetation to accommodate infrastructure, housing, and agriculture. Minor transitions to Open Space (0.0248) and Wetland (0.0099) were also observed, which may result from changes in land management or seasonal hydrological variation.

Wetland emerges as the most stable landcover class, with a self-transition value of 0.8655. This high persistence implies strong ecological resistance to change or the presence of conservation or zoning policies. However, 12.78% of Wetland is expected to convert to Vegetation, which could signal gradual drying, sedimentation, or ecological succession. Transitions to Built-Up (0.0032) and Open Space (0.0036) are extremely rare, confirming the isolation or protected status of wetland zones, see table 7.

Table 7: Landcover/landuse Transition Potential; Matrix

	Built Up Area	Open Space	Vegetation	Wetland
Built Up Area	0.809537699	0.102377133	0.086383744	0.001701424
Open Space	0.649971312	0.081170475	0.265854399	0.003003814
Vegetation	0.13404034	0.024769483	0.831230012	0.009960164
Wetland	0.003184543	0.003585956	0.127756369	0.865473132

The transition matrix reveals critical insights into the dynamics of land transformation in Sapele LGA. Notably, the ANN model confirms that Built-Up Areas are expanding rapidly, with Open Space and Vegetation serving as the most common precursors to urban development. Open Space, in particular, functions as a highly transitional class—frequently targeted for development, yet occasionally reverting to Vegetation depending on land-use pressures and ecological processes.

Vegetation, although relatively stable, is under increasing pressure from built-up expansion, which poses risks to ecological health, biodiversity, and climate resilience. Wetlands, while currently stable, show early warning signs of encroachment and ecological shifts. The transition to Vegetation implies potential wetland degradation or hydrological changes, which may undermine the critical services wetlands provide, such as flood regulation and water purification.

The high validation accuracy of the ANN model ensures that these predictions are both reliable and actionable. These findings offer a valuable decision-support tool for urban planners, environmental managers, and policymakers aiming to balance development with ecological sustainability.

3.6.2 Future Landcover Prediction for the Year 2050 Using Artificial Neural Network (ANN)

The prediction of future landcover conditions for Sapele Local Government Area (LGA) by the year 2050 was achieved using an Artificial Neural Network (ANN) model implemented through the MOLUSCE plugin in QGIS. This model, which was trained on historical landcover data between 2000 and 2025, revealed notable spatial transformations across the major landcover classes: Built-Up Area, Vegetation, Open Space, and Wetland. The results offer insights into the likely trajectory of land development and ecological evolution in the study area over the next quarter century.

According to the ANN-based projection, Built-Up Areas are expected to increase significantly to 123.62 km², accounting for 27.45% of the total land area in Sapele LGA by 2050. This finding indicates a continued and aggressive expansion of urban infrastructure, commercial activities, and residential settlements. The urban footprint, which had already grown steadily between 2000 and 2025, appears poised to extend further into peripheral zones. The predicted growth highlights the persistent influence of population growth, rural-urban migration, and economic development on land transformation. If unregulated, this expansion could lead to environmental degradation, increased surface runoff, heat island effects, and strain on existing infrastructure, see figure 14.

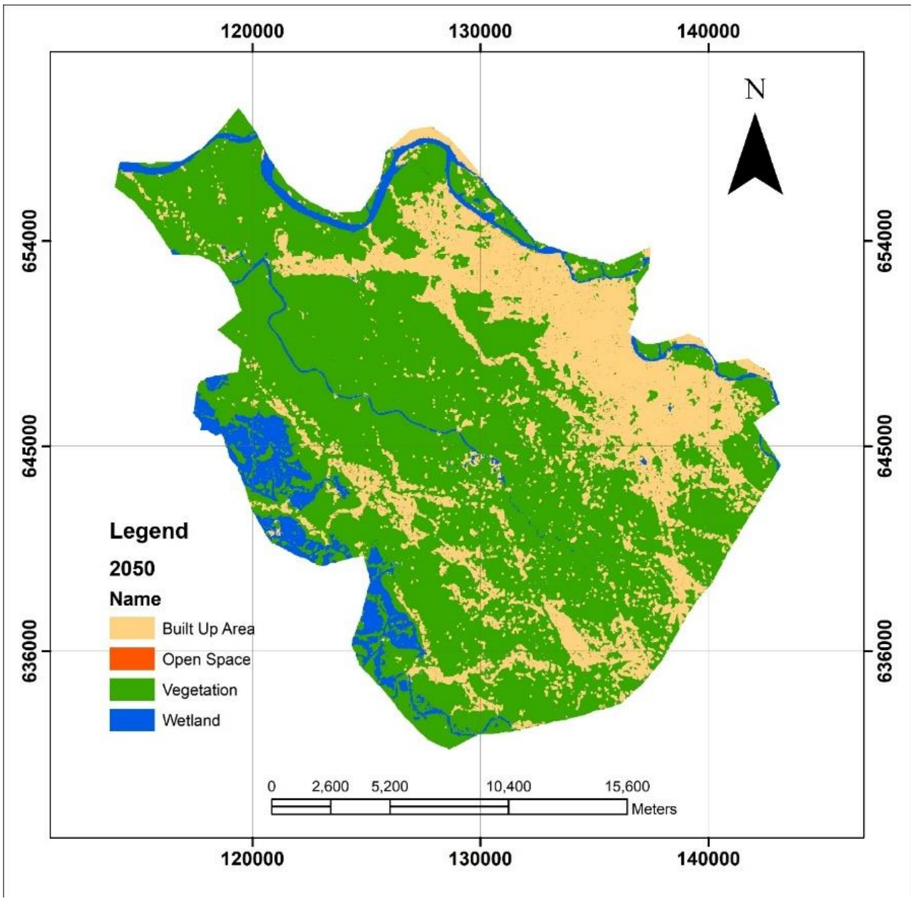

Fig 14: Artificial Neural Network Prediction to 2050

In contrast, the model forecasts an unexpected resurgence of Vegetation, with a projected coverage of 292.74 km², representing 65.00% of the total landscape. This outcome deviates from previous historical trends in which vegetation declined sharply between 2005 and 2025. The projection reflects the natural regeneration of abandoned farmlands or settlements. Nevertheless, the implication of a vegetated landscape dominating over two-thirds of the LGA is both ecologically encouraging and strategically important. It indicated an opportunity to restore ecological balance, improve biodiversity habitats, mitigate climate change impacts through carbon sequestration, and enhance environmental sustainability in the face of expanding urban development.

Another important component of the future landcover structure is Wetland, which is projected to occupy 33.01 km², amounting to 7.33% of the total area. This is relatively stable when compared to the 2025 estimate and indicates that wetland areas will retain their extent due to natural resilience or protective land-use regulations. Wetlands provide critical ecosystem services such as flood control, groundwater recharge, and biodiversity support. Therefore, their continued presence in 2050, albeit modest, will be vital for maintaining hydrological integrity and landscape functionality in Sapele.

The most concerning projection is the near disappearance of Open Space, which is expected to decline drastically to only 0.974 km², making up a negligible 0.22% of the LGA. This loss represents the near-total conversion of undeveloped land to either built-up or vegetated areas. Historically, open spaces have served as transition zones or buffers between land uses, offering flexibility for infrastructure development, agriculture, recreational areas, or ecological corridors. Their projected elimination signals a future in which the landscape becomes highly polarized—dominated by either urban or vegetative cover with minimal room for flexible or low-impact uses. This could undermine spatial equity, reduce urban livability, and eliminate opportunities for future adaptive land use.

Taken together, the ANN model's prediction for 2050 paints a landscape that is more developed, greener in certain zones, and highly organized along functional lines. The expansion of Built-Up Areas and Vegetation indicated a dual narrative of human advancement and potential environmental restoration, while the minimal footprint of Open Space reflects intensified land-use competition. The results emphasize the need for proactive land-use planning, integrated green infrastructure development, and stringent regulatory mechanisms to guide urban expansion and preserve critical ecological zones.

4. Conclusion

The results of this study confirm that Sapele LGA has undergone significant landcover change between 2000 and 2025, driven predominantly by the expansion of built-up areas. This urban growth has come at the cost of vegetative cover and open space, with wetlands remaining relatively stable but vulnerable. The directional analysis confirmed that these changes are not random but follow a dominant North-Northeast progression, suggesting structured urban sprawl along major developmental corridors.

The consistent rise in land use intensity, as captured by the LUI index, signifies increasing pressure on the environment, infrastructure, and land resources. While the ANN prediction for 2050 suggests a possible recovery of vegetation, the almost total loss of open space and continued urban expansion signal future challenges related to urban livability, spatial equity, and ecological sustainability.

This study makes several important contributions to the existing body of knowledge in landcover dynamics, urban geography, and geospatial analysis. First, it demonstrates the utility of Gradient Direction Analysis as a novel tool in detecting both the magnitude and orientation of landscape changes—an aspect often overlooked in traditional landcover change studies. Second, the application of the Land Use Intensity Index (LUI) introduces a quantitative perspective on the degree of anthropogenic transformation, offering a valuable metric for environmental impact assessment.

Additionally, the integration of Artificial Neural Network (ANN) modeling within the MOLUSCE plugin in QGIS for transition potential mapping and prediction introduces an effective framework for spatial forecasting. The use of high-performing ANN parameters, coupled with a strong validation kappa (0.8593), confirms the robustness of machine learning for landcover simulation in data-scarce environments. Lastly, the prediction to 2050 offers empirical insights for long-term planning and supports adaptive policy formulation by urban and environmental management agencies.

5. References

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