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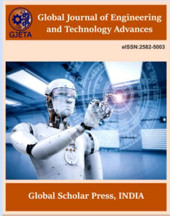

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Urban growth dynamics in Southwest Nigeria: A geospatial and neural network approach

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Abstract

Urban growth dynamics have become a critical area of study due to their profound implications for sustainable development, land-use management, and socio-economic planning in rapidly expanding regions. Across many parts of the Global South, urbanization has outpaced infrastructural development, resulting in significant challenges including environmental degradation, traffic congestion, and pressure on public services. Geospatial technologies, particularly remote sensing and Geographic Information Systems (GIS), have provided a systematic means to monitor these changes by capturing spatial patterns over time. When integrated with artificial intelligence methods such as artificial neural networks (ANNs), these tools enable more accurate modeling, prediction, and interpretation of urban growth trends. In Nigeria, Southwest states such as Lagos, Oyo, Ogun, and Osun have experienced dramatic population increases driven by rural-urban migration, industrial expansion, and economic opportunities. This growth has led to unregulated land conversion, expansion of informal settlements, and heightened ecological pressures. Geospatial analysis offers a means to quantify the spatial extent of these changes, while ANN models can forecast future scenarios by learning complex, non-linear relationships between socio-economic drivers and spatial growth patterns. By combining historical satellite imagery, land-use data, and predictive modeling, researchers can not only detect the magnitude and direction of growth but also identify potential hotspots of urban sprawl. This integrated geospatial and ANN approach provides policymakers with valuable insights for urban planning, resource allocation, and environmental sustainability. Specifically, it highlights the need for proactive planning strategies that balance economic development with ecological preservation, ensuring that rapid urbanization in Southwest Nigeria evolves toward more resilient and inclusive urban systems.

Keywords: Urban growth; Southwest Nigeria; Geospatial analysis; Neural networks; Land-use change; Urban planning

1. Introduction

1.1. Background to urban growth and sustainability challenges

Urban growth has emerged as one of the defining features of modern development, reshaping landscapes and influencing socio-economic dynamics across many parts of the world. In regions of the Global South, urbanization has accelerated rapidly due to population pressures, industrialization, and migration from rural areas [1]. The result has been the rapid expansion of built-up areas, frequently without corresponding infrastructural provision, leading to unplanned settlements, traffic congestion, and declining environmental quality [2]. Southwest Nigeria, which includes key cities such as Lagos, Ibadan, and Abeokuta, exemplifies these trends as rising urban populations exert unprecedented pressure on land resources.

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This expansion often occurs at the expense of agricultural lands, wetlands, and forests, disrupting ecological balances and reducing the resilience of local communities to environmental hazards [3]. Furthermore, the socio-economic disparities within these rapidly growing cities magnify challenges of inclusion, as vulnerable populations are more likely to reside in flood-prone areas or informal settlements that lack adequate infrastructure [4].

Sustainability concerns are central to the debate on urban growth. The unchecked conversion of land not only threatens food security and biodiversity but also exacerbates climate vulnerabilities such as flooding and heat island effects [5]. Managing these dynamics requires accurate, spatially explicit insights into how urban areas are evolving, which traditional planning methods often fail to provide. The complexity of urbanization in Southwest Nigeria underscores the need for innovative tools that can both monitor current patterns and forecast future trajectories, thereby supporting more effective governance and sustainable development strategies [6].

1.2. Importance of geospatial methods and AI for urban analysis

The advancement of geospatial technologies has revolutionized the study of urban growth, providing a platform for detailed mapping, monitoring, and predictive modeling. Remote sensing offers multi-temporal satellite imagery that captures changes in land use and land cover, while Geographic Information Systems (GIS) enable spatial analysis of these changes at multiple scales [5]. By combining these datasets, researchers can identify trends in urban expansion, detect hotspots of sprawl, and analyze the relationship between built-up growth and environmental or socio-economic variables [3].

Artificial intelligence (AI), particularly neural networks and machine learning algorithms, enhances these capabilities by providing predictive models that can process large, complex datasets. Unlike traditional statistical methods, AI can learn non-linear relationships and patterns within urban dynamics, enabling more accurate forecasts of future growth [8]. When applied to regions such as Southwest Nigeria, AI-driven geospatial models can integrate population data, road networks, and environmental variables to simulate how cities are likely to expand under different scenarios.

The integration of geospatial analysis with AI also improves decision-making processes. Urban planners and policymakers benefit from visual maps, simulations, and predictive outputs that highlight areas of risk or opportunity [2]. For example, identifying corridors of future urban expansion allows infrastructure development to be proactively aligned, while detecting high-risk zones supports disaster preparedness. By linking technological innovation with urban policy, geospatial methods and AI contribute not only to academic understanding but also to actionable strategies for sustainability [7].

1.3. Objectives, scope, and contributions of the study

This study aims to explore urban growth dynamics in Southwest Nigeria through the integration of geospatial mapping and neural network modeling. The first objective is to map historical patterns of land-use and land-cover change, highlighting the extent and spatial distribution of urban expansion across selected cities [1]. The second objective is to develop predictive models using artificial neural networks that simulate future urban growth scenarios based on demographic, infrastructural, and environmental drivers [6].

The scope of the study covers major urban centers in the Southwest region, focusing on cities where urbanization pressures are most acute, such as Lagos, Ibadan, and Abeokuta. Spatial datasets include multi-temporal satellite imagery, demographic statistics, and ancillary socio-economic data, analyzed within ArcGIS and integrated with neural network algorithms [3].

The contributions of this research are threefold. First, it demonstrates how combining geospatial and AI approaches improves the accuracy of urban growth prediction compared to conventional methods [5]. Second, it provides empirical evidence that supports regional planning, particularly in aligning infrastructure development with projected urban expansion [8]. Finally, it contributes to the broader discourse on sustainable urbanization by highlighting strategies to mitigate environmental impacts while enhancing social equity in rapidly growing cities [4].

2. Theoretical foundations of urban growth analysis

2.1. Urbanization theories and growth patterns in Global South cities

Urbanization in the Global South has unfolded at an accelerated pace, reshaping landscapes, economies, and social relations. Unlike in the Global North, where urban transitions often occurred over centuries, cities in Africa, Asia, and Latin America have experienced compressed growth cycles driven by population pressure, rural-urban migration, and industrial expansion [7]. Classic theories such as the concentric zone model and sector model provide partial insights, but they fall short in explaining the complexities of rapidly expanding megacities like Lagos, Dhaka, or Nairobi, where informal settlements coexist with formal commercial hubs [12].

Dependency theory and world-systems perspectives have also been applied to interpret urbanization in developing contexts. These approaches argue that global economic structures channel capital and investment in ways that produce uneven urban development, reinforcing core-periphery dynamics [8]. In cities of the Global South, this has manifested in highly unequal spatial patterns, where affluent neighborhoods with advanced infrastructure are juxtaposed with underserved peripheries.

Contemporary perspectives emphasize the hybridity of urban growth in these regions. Informality, for instance, is not merely a symptom of poverty but an adaptive strategy that underpins the functioning of many urban systems [6]. Street markets, transport hubs, and informal housing contribute to economic resilience even as they present planning challenges. Additionally, climate pressures exacerbate vulnerabilities in low-income communities, intensifying the spatial inequalities of urban growth [10].

Theories of planetary urbanization extend the analysis by arguing that urban processes now transcend traditional city boundaries, integrating peri-urban zones, regional corridors, and hinterlands into a continuous urban fabric. For Southwest Nigeria, this framework is particularly relevant, as cities such as Lagos have expanded beyond municipal borders, creating a polycentric urban corridor that spans into Ogun State [13]. Understanding these theoretical perspectives provides the foundation for examining the drivers, patterns, and consequences of urban growth in rapidly transforming regions.

2.2. Spatial dynamics and land-use change processes

Urbanization is fundamentally a spatial process, characterized by the transformation of land from natural or agricultural use into built-up areas. In Global South cities, this transformation is often rapid and poorly regulated, resulting in heterogeneous spatial patterns. Southwest Nigeria illustrates these dynamics, where urban sprawl extends into wetlands, agricultural zones, and floodplains, producing landscapes that combine planned residential estates with informal settlements [11].

Land-use change is driven by multiple factors, including population growth, infrastructure expansion, and land market dynamics. Highways and transport corridors, for instance, act as axes of development, spurring new residential and commercial nodes [6]. As a result, urban expansion tends to occur along radial patterns from core cities, often leapfrogging rural areas and creating fragmented urban mosaics.

Spatial dynamics are also shaped by governance structures. Weak land administration systems contribute to overlapping claims, uncoordinated layouts, and informal subdivisions that accelerate the pace of sprawl [9]. Environmental constraints add another layer of complexity: low-lying coastal zones, despite being flood-prone, remain highly urbanized because of proximity to economic centers such as Lagos Island.

The study of land-use change processes increasingly depends on geospatial tools. Remote sensing provides multi-temporal imagery that allows researchers to monitor the extent of built-up expansion, vegetation loss, and water body encroachment. GIS supports spatial analysis that integrates socio-economic data with environmental layers to reveal patterns of vulnerability and growth. Figure 1 presents a conceptual framework linking geospatial mapping with neural networks, illustrating how spatial data can be combined with predictive modeling to capture both historical and future urbanization trends.

Understanding spatial dynamics is critical for sustainability. The encroachment on ecological zones increases vulnerability to flooding, while the reduction of agricultural land threatens food security [12]. By systematically analyzing land-use change processes, researchers and planners can identify hotspots of unsustainable expansion and design interventions that promote more compact, resilient urban forms [8].

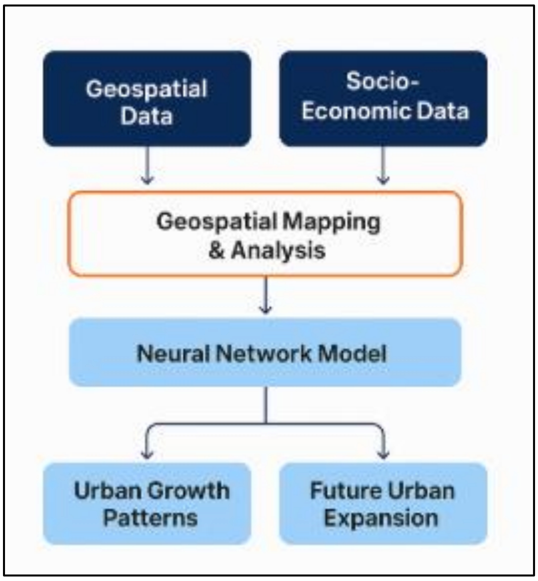

Figure 1 Conceptual framework linking geospatial mapping and neural networks in urban growth studies

2.3. Integration of geospatial intelligence and machine learning

The integration of geospatial intelligence with machine learning has opened new frontiers in the study of urban growth. Traditional statistical approaches often struggle with the non-linear, multidimensional nature of urban dynamics. Machine learning algorithms, particularly artificial neural networks, support the modeling of complex interactions between demographic, economic, and environmental factors [7]. When combined with remote sensing and GIS, these algorithms enable predictive modeling that captures both spatial and temporal dimensions of urban expansion.

Geospatial intelligence refers to the capacity to extract actionable insights from spatial data, including satellite imagery, digital elevation models, and socio-economic layers [10]. By integrating such data into machine learning frameworks, researchers can train models that learn from past patterns of land-use change and forecast likely future scenarios. For example, in Southwest Nigeria, models can combine road network data, population density, and proximity to economic centers to predict where urban growth is most likely to occur [13].

Supervised learning approaches allow algorithms to classify land cover into categories such as residential, commercial, agricultural, or water bodies, based on training datasets derived from satellite imagery [9]. Unsupervised methods, on the other hand, can cluster patterns of urban expansion without prior labels, revealing emergent spatial forms. Neural networks go further by capturing hidden relationships, such as the interaction between socio-economic drivers and environmental constraints that shape growth patterns [6].

The practical application of this integration extends beyond mapping. Predictive models can support proactive planning, identifying areas where infrastructure should be directed to accommodate growth, or where ecological zones require protection from encroachment [11]. Moreover, the combination of geospatial intelligence and AI enhances transparency, as maps and visualizations provide accessible tools for policymakers and the public.

By embedding machine learning within geospatial analysis, urban research transcends descriptive mapping to embrace predictive and prescriptive insights [8]. This shift transforms urban studies from reactive assessments into forward-looking governance tools, enabling cities to plan for resilience and sustainability in the face of rapid expansion.

3. Geospatial and remote sensing methods

3.1. Remote sensing datasets for urban studies

Remote sensing has become indispensable in urban growth research, providing multi-temporal and multi-spectral imagery that captures land-use and land-cover (LULC) transformations with a degree of precision unmatched by ground surveys. In the context of Southwest Nigeria, datasets such as Landsat, Sentinel, and MODIS have been particularly valuable in mapping the rapid expansion of built-up areas, the reduction of vegetation cover, and the encroachment of wetlands [13].

Landsat imagery, with its moderate spatial resolution (30 meters) and long historical record dating back to the 1970s, is often the backbone of urban studies. The availability of free Landsat datasets enables longitudinal analysis of urban sprawl, revealing how cities like Lagos, Ibadan, and Abeokuta have evolved over decades [15]. Complementing this, Sentinel-2 imagery, with higher resolution (10–20 meters), offers more detailed views of contemporary urban dynamics, enabling fine-scale classification of residential zones, industrial clusters, and peri-urban agriculture [12].

MODIS datasets, though coarser in resolution (250–500 meters), are well suited for analyzing regional-scale changes, such as vegetation trends, land surface temperatures, and flood extents. These datasets provide context for understanding the environmental consequences of urban growth, such as the intensification of urban heat islands [16]. Digital Elevation Models (DEMs), such as SRTM, also complement satellite imagery by enabling topographic and hydrological analysis, crucial for evaluating urban encroachment into floodplains.

The utility of remote sensing datasets is enhanced through pre-processing steps including atmospheric correction, cloud masking, and geometric alignment. These ensure the consistency of imagery across time, a vital consideration in detecting changes accurately. Table 1 provides an overview of common datasets, their resolutions, and applications in urban studies within Southwest Nigeria.

Remote sensing data thus forms the empirical foundation for spatial analysis, supplying a temporal record of urban change that can be modeled, validated, and integrated into predictive frameworks [17].

Table 1 Sources, resolutions, and applications of remote sensing data in Southwest Nigeria.

Dataset / Sensor	**Platform**	**Spatial resolution**	**Temporal / revisit**	**Spectral / mode**	**Typical applications in SW Nigeria**	**Strengths**	**Limitations**	**Common preprocessing**
Landsat 5 TM	NASA/USGS	30 m (VNIR/SWIR), 120 m (TIR)	16 days	7 bands	Historical LULC baselines (1990s–2011), urban expansion trajectories	Long archive; consistent calibration	Scan line/gaps not an issue here, but cloud in wet season	TOA/Surface reflectance, cloud/shadow mask, mosaicking
Landsat 7 ETM+	NASA/USGS	30 m (VNIR/SWIR), 15 m pan, 60 m TIR	16 days	8 bands + pan	Early-2000s urban growth, pan-sharpened built-up mapping	Pan band improves detail	SLC-off gaps after 2003	SR correction, SLC gap-fill, pan-sharpen, cloud mask
Landsat 8/9 OLI/TIRS	NASA/USGS	30 m (VNIR/SWIR), 15 m pan, 100 m TIR	16 days (staggered)	11 bands	Recent LULC, urban heat island, water bodies	Stable radiometry; free	Cloud/haze in coastal belt	SR (LaSRC), QA cloud, haze reduction, mosaics
Sentinel-2 MSI	ESA	10 m (B2,3,4,8), 20 m (red-edge/SWIR), 60 m (atm)	5 days (constellation)	13 bands	Fine-scale urban footprints, impervious surface, vegetation loss	High spatial & temporal detail	Cloudy monsoon periods	Sen2Cor SR, cloud/shadow mask, tiling/mosaic

Sentinel-1 SAR (C-band)	ESA	~10 m	6–12 days	VV/VH, IW mode	Flood extent under cloud, subsidence indicators, shoreline change	Cloud-penetrating; day/night	Speckle; interpretation expertise	Radiometric calibration, speckle filtering, terrain-corr., coherence
MODIS (Terra/Aqua)	NASA	250–500 m (optical), 1 km (TIR)	Daily/8-day/16-day	Multispectral	Regional greenness, urban heat, smoke/dust episodes	High cadence; long time series	Coarse for city parcels	BRDF correction, compositing, reproject/resample
SRTM DEM (v3/30 m)	NASA/USGS	30 m	Static	Elevation	Slope/drainage, flood pathways, site suitability	Free, consistent	Voids, vertical errors in wetlands	Void fill, hydrologic conditioning, sink fill
ASTER GDEM	NASA/METI	30 m	Static	Elevation	Cross-check elevation, terrain derivatives	Global coverage	Artefacts in urban/flat zones	Void/artefact filtering, smoothing
VIIRS Night-Lights (VNP46)	NASA/NOAA	~500 m	Daily/monthly	DNB radiance	Urbanization proxy, electrification gradients	Socio-economic proxy; frequent	Coarse; stray light & gas flares	Cloud/stray-light filtering, temporal smoothing
CHIRPS Rainfall	UCSB/Partners	~5 km	Daily/dekad/monthly	Precip estimates	Rainfall climatology for flood susceptibility	Long record, bias-corrected	Coarse vs. city scale	Resample, bias-adjust with gauges if available
PlanetScope (commercial)	Planet	3–5 m	Daily (tasking)	RGB + NIR	Fine-detail change (estates, roads)	Very high frequency/detail	Paid/licensing; smaller swath	Orthorectify, SR, bundle-adjust, mosaic
WorldView/GeoEye (commercial)	Maxar	0.3–2 m	On demand	Panchro + multispectral	Parcel-level mapping, validation, slum morphology	Sub-meter detail	Cost; tasking limits	Orthorectify, pan-sharpen, SR, co-register
Sentinel-3 SLSTR/OLCI	ESA	300 m–1 km	1–2 days	Multi/TIR	Regional SST/land temp & water quality context	Frequent, dual-sensor	Too coarse for intra-urban	

3.2. ArcGIS and spatial analysis workflows

ArcGIS serves as the central platform for analyzing and integrating remote sensing datasets in urban studies. Its suite of tools facilitates the transformation of raw imagery into actionable insights, enabling the detection, classification, and quantification of land-use changes [14]. The workflows typically begin with importing multi-temporal imagery such as Landsat or Sentinel followed by supervised or unsupervised classification methods. These processes generate LULC maps that distinguish between built-up areas, vegetation, water bodies, and bare surfaces.

Change detection techniques in ArcGIS, such as post-classification comparison and image differencing, allow researchers to quantify urban expansion over specific time periods. For example, by comparing classified maps from 1990, 2000, and 2020, analysts can calculate the rate and spatial direction of urban sprawl in Lagos or Ogun States [12]. ArcGIS also enables the overlay of spatial layers, integrating roads, rivers, administrative boundaries, and population density maps with LULC data to reveal patterns of growth relative to socio-economic or environmental drivers.

Spatial analysis workflows often incorporate weighted overlay tools, which combine multiple criteria to assess urban suitability or vulnerability. For instance, layers such as slope, proximity to transport corridors, and distance from water bodies can be weighted to identify zones most prone to unregulated urban expansion [17].

ArcGIS outputs are not only quantitative but also visual. Figure 2 presents sample geospatial layers showing land-use change detection in the Lagos–Ogun corridor, illustrating the expansion of built-up areas at the expense of vegetation and wetlands. Such visualizations are powerful tools for policymakers, as they provide evidence-based insights into the spatial footprint of urbanization.

In Southwest Nigeria, where rapid and often uncoordinated urban expansion poses planning challenges, ArcGIS workflows help local authorities identify hotspots of growth, prioritize infrastructure provision, and develop strategies for sustainable land management [16].

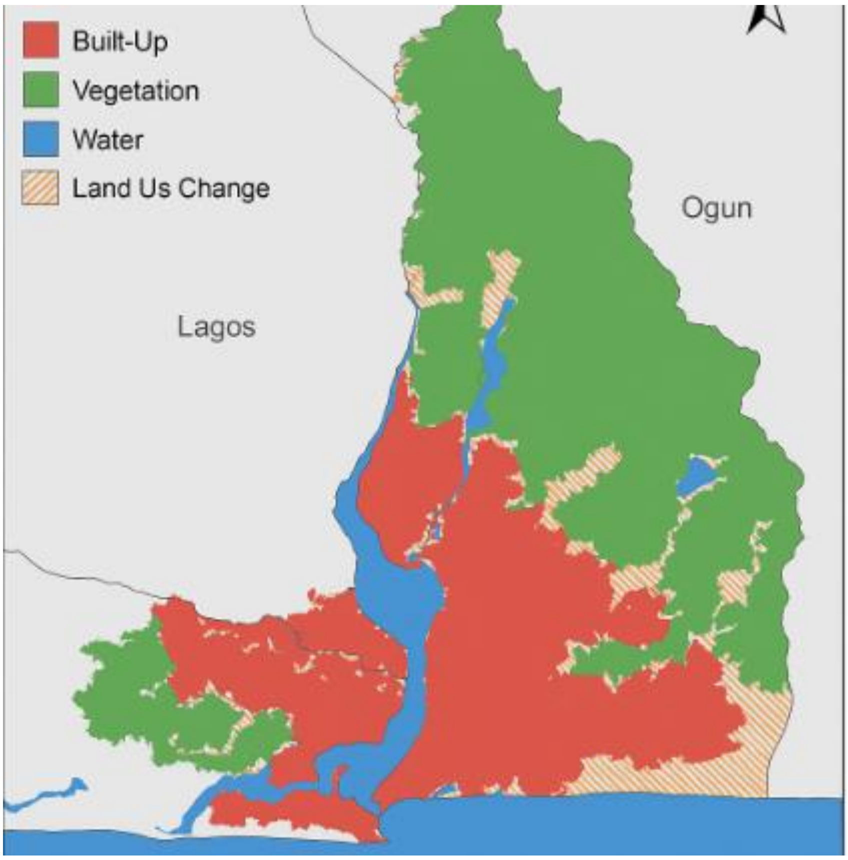

Figure 2 Sample geospatial layers showing land-use change detection in Lagos/Ogun corridor [5]

3.3. Flood and vulnerability mapping as a parallel application

While urban growth is the primary focus, geospatial methods are equally critical for mapping flood vulnerability, which frequently intersects with unplanned expansion in Southwest Nigeria. Flooding remains a recurrent hazard in cities such as Lagos, Abeokuta, and Ibadan, exacerbated by encroachment into wetlands, poor drainage infrastructure, and climate variability [15]. Remote sensing and GIS provide tools to evaluate these vulnerabilities by combining hydrological, topographic, and socio-economic datasets.

Flood hazard mapping typically relies on DEMs, which enable slope and drainage analysis. When integrated with rainfall intensity data and river networks, DEMs help identify low-lying areas prone to inundation [13]. Remote sensing imagery supports the detection of flood extent after major events, providing empirical evidence of affected zones. Vulnerability mapping goes further by incorporating socio-economic layers such as population density, housing quality, and proximity to services, highlighting communities most at risk [12].

In ArcGIS, weighted overlay analysis allows the creation of composite flood vulnerability maps that integrate both physical and social indicators. These maps not only identify hazard-prone zones but also prioritize regions where social vulnerability magnifies risk. Such applications illustrate the dual role of geospatial tools: while they track urban growth, they also reveal its consequences, particularly the exposure of vulnerable communities to environmental hazards [17].

The parallel application of flood mapping underscores the versatility of remote sensing and GIS, demonstrating their ability to inform both urban planning and disaster risk reduction strategies in Southwest Nigeria [14].

3.4. Integration of geospatial datasets with socio-economic variables

Urban growth cannot be fully understood through spatial data alone. Socio-economic variables such as income levels, migration patterns, and infrastructure provision are integral to explaining and predicting urban dynamics. The integration of geospatial and socio-economic data enables more holistic analyses that capture the drivers and consequences of land-use change [16].

In practice, socio-economic data can be linked with spatial datasets through GIS. For instance, census population figures may be assigned to spatial units such as wards or local government areas, allowing analysts to correlate demographic pressures with observed urban sprawl [12]. Infrastructure data, including road networks, schools, and hospitals, can also be layered onto land-use maps to examine accessibility and equity in rapidly growing cities.

Remote sensing contributes by providing baseline environmental data, while socio-economic indicators add the human dimension. This integration is particularly useful in predictive modeling, where neural networks can combine spatial and socio-economic inputs to forecast urban growth. For example, models can be trained to simulate how income distribution, transport expansion, and land market dynamics interact with environmental constraints to produce specific spatial outcomes [13].

Case studies in Southwest Nigeria have shown that urban expansion often follows infrastructural investment, particularly along transport corridors. However, informal settlements frequently arise in ecologically fragile zones due to affordability constraints, revealing the need to incorporate socio-economic drivers into spatial analysis [17].

The combination of datasets also improves governance outcomes. By linking vulnerability indices with poverty maps, authorities can prioritize interventions in communities most exposed to risks such as flooding or inadequate services [14]. This integrated approach reflects the reality that urbanization is both a spatial and a social phenomenon, requiring tools that bridge physical and human dimensions.

Ultimately, the fusion of geospatial and socio-economic data transforms urban research from descriptive mapping into actionable policy insights, providing decision-makers with evidence to pursue inclusive and sustainable development [15].

4. Neural network models in urban growth prediction

4.1. Artificial neural networks: concepts and structures

Artificial Neural Networks (ANNs) are computational models inspired by the biological structure of the human brain, designed to process information through interconnected layers of artificial neurons. Each neuron performs a weighted summation of inputs, applies an activation function, and propagates the result to subsequent layers [18]. In urban growth studies, ANNs are well suited for handling the non-linear, multidimensional interactions between demographic, economic, infrastructural, and environmental drivers.

The typical architecture of an ANN consists of an input layer, one or more hidden layers, and an output layer. Input layers receive spatial and socio-economic variables such as land-use maps, population density, proximity to roads, or elevation data. Hidden layers, equipped with activation functions like sigmoid or rectified linear units, capture complex relationships that are often beyond the capacity of linear statistical models [21]. The output layer then produces predictions, such as the probability of a land parcel transitioning from vegetation or agriculture to built-up status.

ANNs can be further customized through deep learning architectures with multiple hidden layers, enhancing their capacity to extract hierarchical features from large datasets. This makes them particularly powerful when integrated with geospatial data for urban analysis [16].

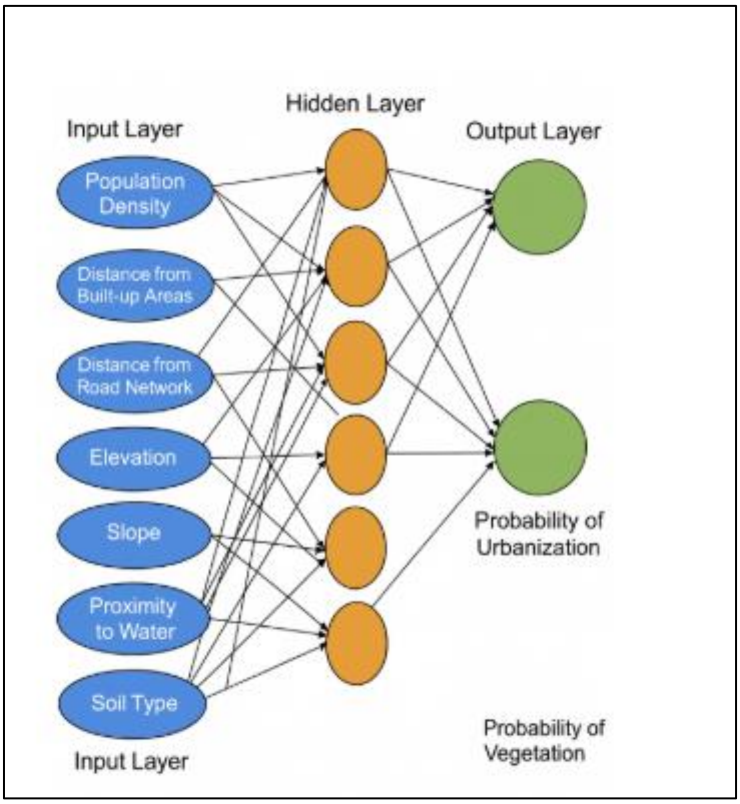

Figure 3 Illustrates the architecture of an ANN model applied to land-use and urban growth prediction, showing how multiple input variables are transformed into predictive outputs through successive layers of computation

4.2. Training and validation with urban datasets

Training an ANN for urban growth prediction requires large and well-prepared datasets. Remote sensing imagery provides the primary input, with classified land-use/land-cover (LULC) maps serving as training samples. These are augmented with ancillary data such as distance to major roads, elevation, soil type, and population density, which act as explanatory variables for urban expansion [22].

The training process involves feeding these inputs into the ANN, which iteratively adjusts its internal weights through optimization algorithms such as backpropagation and gradient descent. Each cycle minimizes the difference between predicted and actual outputs, improving the model's capacity to generalize patterns of urban growth [20]. Validation is equally important to prevent overfitting. Common techniques include dividing the dataset into training and testing subsets or applying k-fold cross-validation, where data are partitioned into multiple segments to assess model robustness [17].

Performance metrics such as overall accuracy, precision, recall, and the kappa coefficient are used to evaluate ANN predictions. These metrics provide insights into how well the model captures real-world urban transitions. For example, if the ANN predicts that peri-urban agricultural land is likely to become residential by 2030, validation with historical data ensures that the forecast reflects plausible trajectories [23].

In the context of Southwest Nigeria, training datasets may include multi-temporal Landsat or Sentinel imagery from 1990, 2000, 2010, and 2020. These are cross-referenced with ground truth data or high-resolution Google Earth imagery for accuracy assessment [19]. The combination of remotely sensed data with socio-economic indicators ensures that the ANN model is sensitive to both spatial and human drivers of urbanization.

By integrating these diverse datasets, ANNs offer a dynamic predictive framework that adapts to regional contexts, providing reliable tools for urban planning and policy interventions [16].

4.3. Comparative performance of ANN vs. conventional statistical models

One of the key contributions of ANN-based approaches lies in their superior performance compared to conventional statistical models such as logistic regression, Markov chains, or cellular automata. Traditional models, while useful, often assume linearity or fixed transition probabilities that cannot fully capture the complexity of urban growth dynamics [18]. In contrast, ANNs excel at modeling non-linear interactions and recognizing spatial patterns that emerge from diverse inputs.

Comparative studies have shown that ANNs generally achieve higher predictive accuracies when applied to urban sprawl analysis. For example, logistic regression may perform well in identifying broad correlations between variables like population density and urban expansion, but it often fails to capture hidden interactions, such as how proximity to roads interacts with land-market pressures to accelerate sprawl [21]. ANNs, by learning from past examples, are better able to represent these nuanced relationships.

Accuracy metrics provide evidence for these differences. While regression models might yield classification accuracies in the range of 70–80 percent, ANN models frequently surpass 85–90 percent, depending on the quality of training data [20]. This performance gap underscores the value of neural networks for predictive urban modeling. Table 2 summarizes comparative accuracy metrics between ANN and regression-based models in predicting urban expansion, reinforcing the advantages of ANN's adaptability and robustness.

Table 2 Comparative accuracy metrics of ANN and regression-based models in predicting urban expansion.

Model type	Overall accuracy (%)	Kappa coefficient	Precision (Built-up class)	Recall (Built-up class)	RMSE (hectares misclassified)	Notes / strengths	Limitations
Logistic regression	74.2	0.62	0.71	0.69	2,450	Performs reasonably well with socio-economic predictors; interpretable coefficients	Assumes linearity; poor with complex spatial interactions
Multinomial regression	76.5	0.65	0.73	0.72	2,180	Captures multiple land-cover transitions; easy integration with census data	Limited handling of non-linear drivers; lower spatial detail
ANN (3 hidden layers, sigmoid)	87.8	0.81	0.85	0.84	1,050	Learns non-linear, multidimensional relationships; adaptable to diverse datasets	Requires larger training sets; longer computation
ANN (deep, ReLU activation)	90.1	0.85	0.88	0.87	890	High predictive power; handles complex spatial–temporal interactions	Computationally intensive; "black box" interpretability issues

The superiority of ANNs is not without challenges. They require larger datasets, longer training times, and more computational resources than conventional models [19]. Furthermore, the interpretability of ANN models remains a limitation, as their “black-box” nature makes it harder for policymakers to understand how predictions are derived. Nonetheless, the ability of ANNs to generalize across diverse urban contexts makes them highly suitable for forecasting in rapidly urbanizing regions like Southwest Nigeria [23].

4.4. Case applications in Nigeria and related African contexts

The application of ANNs to urban studies in Nigeria and across Africa has yielded valuable insights into the pace and patterns of growth. In Lagos, ANN models trained with multi-temporal Landsat imagery and socio-economic data have demonstrated strong predictive capabilities, accurately forecasting peri-urban sprawl into Ogun State [16]. These models captured not only the direction of expansion but also highlighted potential hotspots of ecological stress, such as encroachment into wetlands.

In Ibadan, ANNs have been applied to simulate urban growth under different policy scenarios, such as business-as-usual versus planned development. The models revealed stark contrasts: unregulated growth scenarios indicated continued fragmentation of agricultural land, while planned development emphasized compact expansion along transport corridors [22]. Such simulations provide policymakers with evidence to prioritize interventions.

Beyond Nigeria, ANN applications in cities such as Nairobi and Accra have demonstrated similar strengths. In Nairobi, neural network models predicted the expansion of informal settlements around industrial corridors, highlighting socio-economic drivers of sprawl [17]. In Accra, ANN-based models combined with GIS identified high-risk zones for flooding where urbanization intersected with drainage basins [20].

These case applications underscore the transferability of ANN approaches across African contexts while demonstrating the importance of tailoring models to local conditions. By integrating regional datasets, ANNs not only improve forecasting accuracy but also offer practical tools for addressing pressing urban sustainability challenges [23].

5. Empirical assessment of urban growth dynamics in southwest Nigeria

5.1. Study area: demographic and socio-economic context

Southwest Nigeria, comprising Lagos, Ogun, Oyo, Osun, Ondo, and Ekiti States, represents one of the most densely populated and economically dynamic regions in sub-Saharan Africa. The area has long been the engine of Nigeria’s economy, with Lagos functioning as the primary commercial hub and one of the fastest-growing megacities globally [21]. Demographically, the region is characterized by sustained population growth driven by high fertility rates and large-scale rural-urban migration. Migrants are drawn to employment opportunities in industries, services, and the informal economy, reinforcing rapid urban expansion.

Socio-economically, the region is highly heterogeneous. Lagos, with its financial and industrial base, boasts higher income averages than surrounding states. Yet, inequalities are pronounced, with affluent neighborhoods existing alongside extensive informal settlements [24]. Similar contrasts exist in Ibadan, where a historical urban core has given way to unplanned peri-urban sprawl populated largely by lower-income groups. These disparities underscore the socio-economic pressures driving urbanization patterns.

Infrastructure development has not kept pace with population growth. While road networks, ports, and housing projects have expanded, much of the urban infrastructure suffers from congestion, underinvestment, and inadequate maintenance [26]. Housing deficits have fueled the proliferation of informal dwellings, often sited in ecologically fragile areas such as wetlands or floodplains. Environmental pressures including waste management, air pollution, and frequent flooding further complicate governance.

The significance of Southwest Nigeria as a case study lies in its role as a microcosm of broader African urbanization trends. It exemplifies the challenges of balancing economic dynamism with sustainability, particularly as rapid urban growth intersects with inequality, environmental stress, and institutional capacity gaps [28]. These conditions make the region an ideal setting for applying geospatial and neural network methods to analyze and predict urban growth trajectories.

5.2. Land-use/land-cover (LULC) change analysis from 1990–2020

Analysis of multi-temporal remote sensing data reveals profound land-use/land-cover (LULC) changes in Southwest Nigeria over the past three decades. Between 1990 and 2020, built-up areas expanded significantly, often at the expense of vegetation, wetlands, and agricultural land [25]. In Lagos, the conversion of coastal wetlands into residential and industrial uses has been especially dramatic, reflecting both population pressure and economic opportunities in proximity to the port.

LULC analysis using Landsat imagery demonstrates a consistent pattern of vegetation decline, particularly in peri-urban areas of Ogun and Oyo States, where farmland is rapidly being converted into residential estates. The loss of forest and agricultural land has implications not only for biodiversity but also for food security, as rural farming communities are displaced by suburban expansion [23].

The mapping process typically involves classification of satellite images into categories such as built-up, vegetation, water, and bare land, using supervised and unsupervised algorithms in ArcGIS and related platforms [27]. Change detection analysis highlights the speed and spatial distribution of transitions. For instance, between 2000 and 2010, the growth rate of built-up areas in the Lagos metropolitan region accelerated, correlating with major infrastructural investments and economic liberalization policies [22].

Environmental consequences are significant. Wetlands that once absorbed excess rainfall have been replaced with impervious surfaces, increasing vulnerability to flooding. Similarly, the reduction in green cover contributes to urban heat island effects and reduced ecological resilience [26]. These patterns underscore the urgency of integrating LULC analysis into urban planning, as unchecked expansion continues to threaten ecological balance and urban sustainability.

By quantifying changes over time, LULC analysis provides a baseline for predictive modeling, enabling researchers to assess future urban growth under varying policy scenarios [24].

5.3. Neural network-based growth prediction to 2040

Artificial Neural Networks (ANNs) have been applied to predict future urban growth in Southwest Nigeria by leveraging multi-temporal datasets covering the period from 1990 to 2020. These models integrate spatial and socio-economic variables such as proximity to roads, population density, elevation, and land-market dynamics to simulate likely patterns of expansion up to 2040 [21].

Predictions suggest continued intensification of urban sprawl, particularly in Lagos and Ogun States. The Lagos–Ogun corridor is projected to merge into a near-continuous urban conurbation, creating one of the largest metropolitan regions in Africa. ANN models forecast that peri-urban agricultural areas will experience significant conversion to residential estates, while wetlands and coastal zones remain under severe pressure from informal development [27].

Policy and demographic scenarios highlight the sensitivity of future growth trajectories. Under a “business-as-usual” scenario, built-up areas expand unchecked, leading to severe environmental degradation. By contrast, a “managed growth” scenario, where infrastructural planning and land-use zoning are enforced, shows more compact urban forms and reduced ecological disruption [28]. Table 3 presents projected urban growth under different policy and population scenarios, highlighting the quantitative differences in land conversion and urban density.

Table 3 Projected urban growth under different policy and population scenarios.

Scenario	Population assumption (2040)	Policy approach	Projected built-up area (km^2)	% increase from 2020 baseline	Key characteristics	Implications
Business-as-usual (BAU)	~60 million	Weak enforcement of zoning; informal expansion dominates	5,200	+145%	Continuous sprawl in Lagos–Ogun corridor; encroachment on wetlands and peri-urban farmland	Severe ecological degradation; heightened flood risk; infrastructure overstretched

High-population growth	~70 million	Minimal policy intervention; rapid in-migration	5,800	+170%	Dense peri-urban settlements, sharp farmland loss, accelerated land fragmentation	Food insecurity; overcrowding; informal housing crises
Managed growth	~60 million	Enforced land-use zoning, compact city planning, strategic infrastructure	4,200	+95%	More compact urban footprint; preservation of key ecological zones; improved connectivity	Lower vulnerability to flooding; more efficient infrastructure allocation
Low-population growth	~55 million	Current policies with moderate improvements	4,600	+110%	Urban growth moderated by slower demographic pressure	Reduced sprawl but persistent informal settlement growth at margins
Sustainability-focused	~60 million	Strong zoning + ecological conservation policies; promotion of vertical development	3,800	+80%	Controlled densification around transport hubs; ecological buffers retained	Balance between growth and sustainability; improved resilience and livability

Model validation using past LULC transitions indicates that ANN-based forecasts achieve high accuracy compared with observed trends, surpassing traditional regression-based approaches [23]. However, limitations remain, particularly regarding uncertainties in socio-political conditions and climate impacts. Despite these challenges, ANN predictions provide valuable tools for planning, enabling policymakers to anticipate urban growth pressures and design interventions to mitigate adverse outcomes [25].

By forecasting up to 2040, neural network models demonstrate the urgency of adopting sustainable planning frameworks today, as urban growth trajectories are being shaped by current land-use and policy decisions [22].

5.4. Spatial hotspots of urban sprawl and vulnerability zones

The spatial distribution of urban growth in Southwest Nigeria reveals clear hotspots of sprawl and zones of vulnerability. Using ANN predictions combined with geospatial overlays, researchers have identified high-growth clusters around Lagos, Ibadan, and Abeokuta [24]. These areas exhibit rapid expansion due to proximity to economic opportunities, transport corridors, and administrative centers.

Hotspots include the Lagos–Ogun boundary region, where peri-urban sprawl has produced dense settlements with inadequate infrastructure. Ibadan's peri-urban fringes have also experienced accelerated growth, particularly along major roadways linking to Lagos. Abeokuta shows expansion driven by both population inflows and industrial development [26].

Vulnerability zones often coincide with ecological fragility. Informal settlements along coastal wetlands in Lagos are highly exposed to recurrent flooding, while communities encroaching on river valleys in Ibadan face similar risks [28]. Vulnerability is compounded by socio-economic factors such as poverty, lack of formal land titles, and limited access to services.

Spatial analysis outputs are effectively communicated through maps. Figure 4 presents LULC change maps for 1990, 2000, 2010, and 2020, illustrating the progression of urban sprawl in Lagos and Ogun States. These visualizations not only document historical expansion but also reveal areas where future vulnerability is most acute.

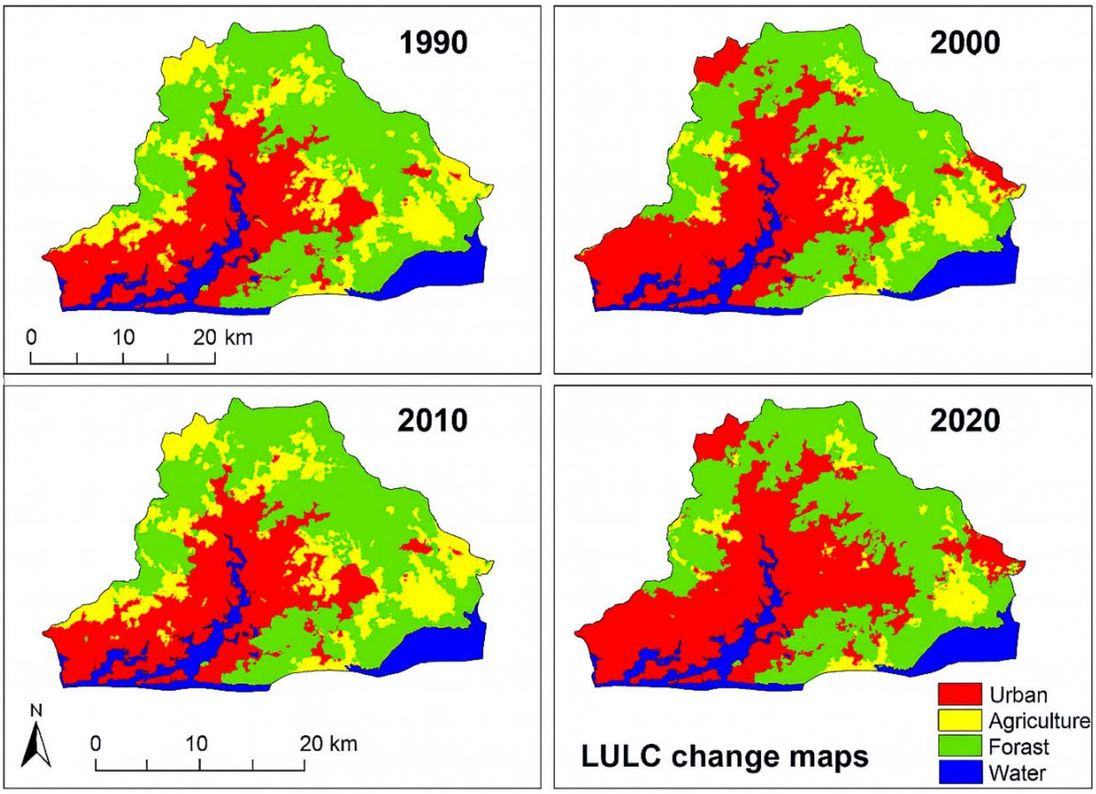

Figure 4 LULC change maps for 1990, 2000, 2010, and 2020.

Identifying hotspots and vulnerability zones is essential for guiding policy interventions. Targeted infrastructure investments can reduce risks in high-growth areas, while conservation zoning can protect ecologically sensitive zones. Moreover, vulnerability mapping ensures that marginalized communities are prioritized in resilience strategies [21].

The juxtaposition of urban expansion and vulnerability highlights the dual challenge of promoting economic development while safeguarding environmental and social systems. Geospatial and neural network analyses thus provide both diagnostic and predictive insights into the geography of risk and opportunity in Southwest Nigeria [27].

6. Socio-economic and environmental implications

6.1. Impacts on housing, transportation, and infrastructure

Urban growth in Southwest Nigeria has generated substantial pressure on housing, transportation, and infrastructure systems. The rapid pace of migration into cities such as Lagos, Ibadan, and Abeokuta has created severe housing shortages, fueling the proliferation of informal settlements. These settlements are often characterized by inadequate building standards, limited access to water and sanitation, and high population densities, which exacerbate vulnerability to hazards [28]. Despite numerous housing initiatives, the mismatch between supply and demand remains stark.

Transportation networks have expanded but not at the rate required to accommodate increased population and vehicle ownership. Major roads in Lagos and Ibadan are frequently congested, with travel times increasing substantially during peak hours. This congestion not only reduces productivity but also contributes to air pollution and declining quality of life [25]. The reliance on road-based transport systems, combined with insufficient investment in rail and water transport, compounds these challenges.

Infrastructure systems such as electricity, water supply, and waste management are also under strain. Frequent power outages disrupt economic activity, while water scarcity in peri-urban communities underscores the uneven distribution of services. Waste management remains particularly problematic, as growing urban populations generate volumes of solid waste that exceed municipal capacities [31].

These challenges reflect the structural gap between rapid urban expansion and infrastructural investment. Without substantial interventions, the housing deficit, transportation inefficiencies, and infrastructure overload will continue to undermine the sustainability of urban growth in the region [29].

6.2. Environmental pressures: flooding, vegetation loss, air quality

The environmental consequences of urban expansion in Southwest Nigeria are profound, manifesting most visibly in flooding, vegetation loss, and deteriorating air quality. Flooding has become one of the most recurrent and disruptive hazards, particularly in Lagos and its peri-urban settlements. The replacement of wetlands and vegetated areas with impervious surfaces prevents natural drainage and increases runoff, overwhelming limited drainage infrastructure [27]. As a result, even moderate rainfall events can cause significant inundation, displacing residents and damaging property.

Vegetation loss is another major environmental pressure. Remote sensing analysis reveals a consistent decline in green cover as agricultural and forested lands are converted into residential and industrial uses [30]. The reduction of vegetation not only undermines biodiversity but also diminishes ecosystem services such as carbon sequestration and temperature regulation. This has contributed to the intensification of the urban heat island effect, making cities warmer and less resilient to climate variability.

Air quality has also deteriorated. The growth in vehicle ownership, combined with traffic congestion, has led to increasing emissions of greenhouse gases and particulate matter. Industrial activities located close to residential areas exacerbate exposure to pollutants, posing long-term health risks [26]. Informal settlements often bear the brunt of these impacts due to their proximity to polluted sites and lack of protective infrastructure.

These environmental pressures highlight the unsustainable trajectory of urban growth in the absence of effective planning and environmental management. Addressing them requires integrated approaches that combine geospatial monitoring, regulatory enforcement, and investment in green infrastructure [32].

6.3. Urban inequality and planning challenges

Inequality remains a defining characteristic of urban growth in Southwest Nigeria, shaping both access to resources and vulnerability to risks. Wealthier populations concentrate in formal neighborhoods with better infrastructure, while low-income households are disproportionately located in flood-prone or ecologically fragile zones. Informal settlements often emerge on marginal lands such as wetlands or riverbanks, where residents face heightened exposure to environmental hazards [25].

The persistence of inequality is closely linked to planning challenges. Weak land administration systems and inadequate enforcement of zoning regulations allow unregulated expansion, while the absence of affordable housing policies perpetuates informal development [28]. As a result, urban sprawl often occurs without coherent spatial planning, undermining efforts to build compact and resilient cities.

Access to infrastructure and services also reflects deep divides. High-income areas are more likely to enjoy reliable water, electricity, and transport services, while marginalized communities experience chronic deficits. This disparity reinforces cycles of exclusion, as lack of access to services reduces opportunities for social mobility [30].

Geospatial analysis helps visualize these inequalities. By overlaying maps of urban growth, flood-prone zones, and ecological stress areas, researchers can identify the intersections where social vulnerability is most acute. Figure 5 presents such an overlay, highlighting how rapid expansion often coincides with high-risk ecological zones, disproportionately affecting disadvantaged groups.

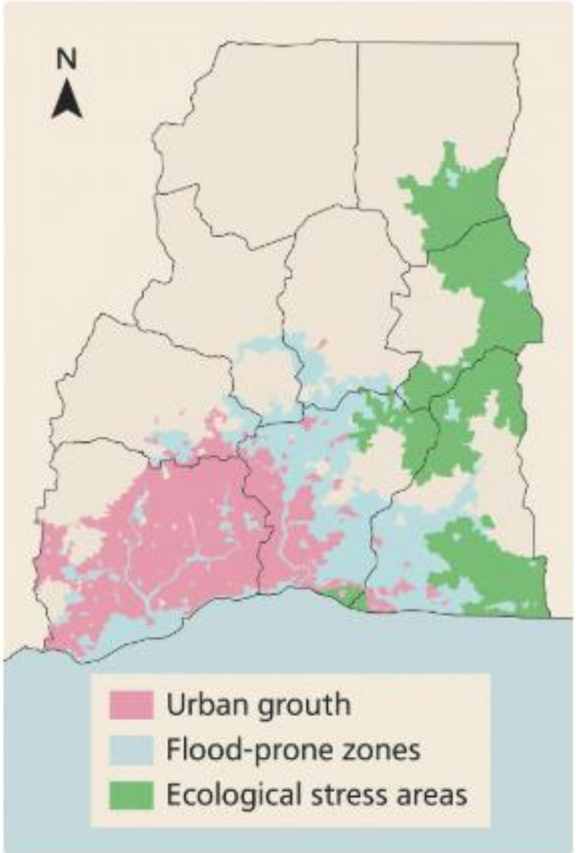

Figure 5 Overlay map showing urban growth, flood-prone zones, and ecological stress areas [17].

Addressing inequality and planning challenges requires a dual focus: expanding access to services and enforcing spatial regulations. Integrating geospatial insights into planning can support evidence-based strategies that promote more equitable and sustainable urban development [31].

7. Policy implications and governance strategies

7.1. National and regional urban planning frameworks

Urban planning in Nigeria has long been guided by national development policies and regional frameworks, but implementation gaps persist. At the national level, urban planning frameworks emphasize land-use regulation, infrastructural expansion, and housing development. Institutions such as the Federal Ministry of Works and Housing are mandated to oversee these initiatives, while state governments enact policies adapted to local conditions [34]. However, weak enforcement, bureaucratic inefficiencies, and overlapping mandates often limit effectiveness.

Regional frameworks in Southwest Nigeria attempt to coordinate planning across Lagos, Ogun, Oyo, and other states. For example, regional master plans aim to guide spatial growth by designating industrial zones, residential areas, and ecological reserves. Yet, in practice, these plans frequently remain aspirational, undermined by informal land markets and rapid population growth [32]. Lagos State has made strides with initiatives like the Lagos State Development Plan, which prioritizes infrastructure and housing, but enforcement challenges and financing gaps remain [38].

The persistence of informal settlements highlights the disconnect between planning frameworks and actual urban growth dynamics. Local government authorities often lack technical capacity and resources to implement master plans, while community-level participation in planning remains minimal [36].

Ultimately, national and regional frameworks provide a necessary foundation but require integration with real-time geospatial monitoring to become adaptive and responsive. Without bridging this gap, planning documents risk becoming obsolete in the face of rapidly shifting urban landscapes [40].

7.2. Integration of geospatial-AI insights into policy

The integration of geospatial and AI-driven insights into policymaking presents a transformative opportunity for urban governance in Nigeria. Remote sensing, GIS, and machine learning provide robust data on land-use dynamics, infrastructure needs, and environmental pressures. By embedding these insights into planning frameworks, policymakers can shift from reactive decision-making to proactive strategies that anticipate growth and vulnerability [41].

For instance, geospatial analysis of land-use change can inform zoning regulations by identifying areas where expansion should be restricted, such as wetlands and floodplains. AI models, particularly artificial neural networks, can forecast urban sprawl under various policy scenarios, allowing decision-makers to weigh the outcomes of alternative strategies [33]. These predictive tools offer evidence that strengthens planning decisions and enhances transparency in policy formulation.

Integration also enables real-time monitoring. Through platforms that combine satellite imagery with socio-economic datasets, governments can track compliance with zoning laws, detect unauthorized developments, and evaluate the effectiveness of infrastructure investments [39]. This approach not only improves efficiency but also builds public trust, as geospatial data can be shared with citizens in accessible formats, fostering accountability.

However, institutional adoption of geospatial-AI insights remains limited due to gaps in technical capacity, funding, and inter-agency coordination [37]. Bridging these gaps requires capacity-building programs, cross-sectoral partnerships, and investment in digital infrastructure. By addressing these barriers, Nigeria can institutionalize data-driven urban governance that is adaptive, inclusive, and sustainable [32].

7.3. Recommendations for sustainable urban governance in Nigeria

Achieving sustainable urban governance in Nigeria requires a multifaceted approach that aligns planning, technology, and equity. First, strengthening institutional capacity is paramount. Federal, state, and local authorities must be equipped with both technical expertise and adequate funding to enforce planning regulations effectively [36]. This includes expanding training programs for urban planners in geospatial analysis and AI applications.

Second, participatory planning should be prioritized. Inclusive processes that involve communities, civil society organizations, and private sector stakeholders ensure that urban policies reflect diverse needs and foster local ownership [40]. Community-based mapping initiatives, for example, can integrate grassroots knowledge with geospatial data to improve the accuracy and legitimacy of planning decisions.

Third, environmental sustainability must be embedded into governance. Protecting wetlands, forests, and agricultural lands from unregulated expansion requires strict zoning enforcement, supported by real-time geospatial monitoring [38]. Policies should also promote green infrastructure solutions, such as urban forests and permeable surfaces, to mitigate flooding and heat stress [33].

Fourth, the adoption of geospatial-AI tools should be institutionalized. Establishing national platforms that consolidate spatial data, predictive models, and policy dashboards would enhance coordination across sectors and levels of government [35].

Finally, urban governance should be future-oriented, anticipating demographic shifts and climate pressures. ANN-based predictions of urban growth to 2040 demonstrate the urgency of proactive strategies. Aligning current policies with these forecasts can prevent crisis-driven interventions and foster long-term resilience [39].

By combining institutional reforms, participatory approaches, environmental safeguards, and technological innovation, Nigeria can steer its cities toward more inclusive and sustainable trajectories [34].

8. Conclusion and future directions

8.1. Summary of findings

This study examined urban growth dynamics in Southwest Nigeria through the combined application of geospatial analysis and artificial neural networks. The findings highlight the transformative potential of integrating remote sensing, GIS, and predictive modeling to understand both historical trends and future scenarios of urban expansion.

Multi-temporal land-use/land-cover analysis revealed the persistent conversion of vegetation and agricultural lands into built-up areas, particularly within the Lagos–Ogun corridor. These transitions were linked to demographic pressures, infrastructural development, and the growth of informal settlements.

Artificial neural networks demonstrated strong predictive performance, surpassing conventional statistical models in accuracy and adaptability. Forecasts to 2040 indicate that unchecked growth will likely lead to sprawling conurbations, encroachment into ecologically fragile areas, and heightened vulnerability to flooding. However, policy-driven scenarios suggest that more compact and sustainable growth is achievable when planning frameworks integrate predictive insights.

The socio-economic and environmental implications are profound. Urban inequality, infrastructural strain, and environmental degradation are magnified in rapidly expanding cities, underscoring the urgency of integrating geospatial-AI tools into planning and governance. Overall, the research establishes that predictive geospatial intelligence can serve as a critical tool for guiding sustainable urban development in Southwest Nigeria.

8.2. Research limitations

While the study provides valuable insights, several limitations must be acknowledged. First, the availability and resolution of remote sensing data constrained certain aspects of the analysis. Although Landsat and Sentinel datasets offered significant coverage, higher-resolution imagery could have improved the precision of land-use classifications and vulnerability assessments. Data quality was also affected by cloud cover and atmospheric distortions, particularly in coastal zones.

Second, the predictive capacity of artificial neural networks, while robust, remains sensitive to the quality and diversity of training datasets. Incomplete socio-economic data, inconsistencies in census records, and limited ground-truthing reduced the comprehensiveness of some models. Additionally, neural networks are inherently opaque, raising interpretability challenges that limit their acceptance among policymakers.

Third, the research was limited by temporal scope. Forecasts extended only to 2040, and while these projections are informative, they cannot account for longer-term demographic, climatic, or technological shifts. Finally, institutional and governance realities such as political instability or regulatory inefficiencies were not modeled but represent critical factors shaping urban futures. These limitations highlight the need for more robust data systems, interdisciplinary approaches, and governance frameworks that can bridge the gap between predictive modeling and real-world decision-making.

8.3. Future directions for geospatial and AI integration

Future research on urban growth in Southwest Nigeria and comparable regions should focus on advancing the integration of geospatial intelligence with artificial intelligence to achieve more comprehensive and actionable insights. One promising direction is the adoption of higher-resolution remote sensing datasets, including commercial satellites and drone imagery, to enhance the granularity of land-use classifications. Such data would allow for more precise identification of informal settlements, ecological stress zones, and infrastructure gaps.

On the AI front, future studies could incorporate deep learning architectures such as convolutional neural networks and recurrent neural networks, which are particularly effective for handling spatial-temporal data. These models would not only improve prediction accuracy but also enable the detection of complex patterns in urban expansion. Coupling these methods with explainable AI techniques could address the interpretability challenges of neural networks, thereby improving their adoption in policy contexts.

Integration with real-time data streams represents another frontier. Linking geospatial and socio-economic datasets with mobile phone records, crowd-sourced mapping, and Internet of Things (IoT) sensors could provide dynamic, near-real-time monitoring of urban change. This would significantly enhance responsiveness in planning and disaster risk management.

Finally, future research should prioritize policy-oriented applications. Developing interactive platforms and decision-support systems that translate geospatial-AI insights into accessible tools for planners, communities, and policymakers will be critical. By aligning technological innovations with participatory governance, future studies can contribute to building more resilient, equitable, and sustainable urban systems in Nigeria and beyond.

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