Geo AI-Assisted Housing Growth Planning and Architectural Neighbourhood Design in Nigerian Secondary Cities Through an Integrated Framework

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ABSTRACT

Nigeria's secondary cities face fragmented expansion, under-serviced housing layouts, environmental exposure and uneven infrastructure provision. This critical structured narrative review examines how GeoAI and complementary geospatial decision-support methods can support housing-growth planning and architectural neighbourhood design in Nigerian secondary cities through an integrated architecture-planning lens. The analytical corpus comprises 46 peer-reviewed articles published between 2010 and 2025, supplemented by methodological, policy, statutory and governance sources. Evidence is synthesised across urban-growth modelling, conventional remote sensing and GIS, GeoAI/machine-learning applications, planning-support systems, housing-location suitability, infrastructure sequencing, Nigerian urbanisation and responsible-AI governance. The synthesis indicates that geospatial analysis can identify growth pressure, service gaps, environmental constraints and candidate housing locations, while GeoAI-specific methods may additionally support classification, prediction and pattern recognition where suitable data and validation procedures are available. Spatial suitability, however, does not itself produce a liveable neighbourhood. Within the proposed framework, Urban and Regional Planning interprets land-use suitability, infrastructure sequencing, participation and development-control requirements. At the same time, Architecture translates preferred planning options into climate-responsive, service-aware and socially liveable neighbourhood alternatives. The paper proposes a testable staged adoption pathway beginning with verified spatial data, explicit decision criteria, professional interpretation, architectural design testing and participatory validation before advanced predictive GeoAI functions are institutionalised. Ado-Ekiti is used only as an illustrative application, not an empirical case study.

Keywords: architecture, GeoAI, geospatial decision support, neighbourhood design, housing growth planning, urban and regional planning, housing-site suitability, secondary cities, Nigeria.

INTRODUCTION

Urban growth management is increasingly important in Nigerian secondary cities as population growth and urbanisation increase demand for serviced land, housing, roads, drainage, schools, markets and healthcare infrastructure (Aliyu & Amadu, 2017; United Nations Department of Economic and Social Affairs, 2019). Although national debate often centres on the largest metropolitan areas, state capitals such as Ado-Ekiti and Akure also experience outward settlement growth and land-use conversion. Remote-sensing studies document substantial change in these cities, including built-up expansion, vegetation loss and institution-induced development (Ajagbe et al., 2021; Balogun et al., 2011; Ogunleye & Owoeye, 2015; Olofin & Oluwadare, 2022).

For this review, secondary cities are defined analytically as non-primary urban centres that perform significant administrative, economic and service functions within their regions but operate below the scale and national dominance of Nigeria's largest metropolitan areas. This working definition is not a statutory classification, and cities included under it are not assumed to have equivalent population size, growth trajectories, institutional capacity or infrastructure conditions.

A central planning challenge is the conversion of land for urban development before infrastructure capacity, environmental risk and access to daily services have been adequately assessed. Uncoordinated expansion can produce under-serviced layouts, costly retrofitting, flood exposure and housing that is physically distant from jobs, schools, markets and public transport. Spatial evidence is therefore needed before major housing locations and infrastructure extensions are committed (Alves et al., 2020; Davern et al., 2017; Parry et al., 2018). Planning-support systems can strengthen anticipatory planning through spatial diagnosis and scenario comparison, while AI-specific methods may augment prediction, classification and pattern recognition (Geertman & Stillwell, 2020; Othengrafen et al., 2025; Sanchez et al., 2023).

In this review, GeoAI refers specifically to AI- or machine-learning methods applied to geospatial data for tasks such as classification, prediction, clustering or pattern recognition. Conventional GIS, remote sensing, cellular automata, spatial multicriteria analysis and scenario modelling are treated as complementary geospatial methods rather than GeoAI in themselves (Casali et al., 2022; Chaturvedi & de Vries, 2021; Masoumi & van Genderen, 2024; Mortaheb & Jankowski, 2023). GeoAI workflows can analyse or combine information derived from satellite imagery, cadastral and land-use records, infrastructure networks, population estimates, hazard layers, building footprints and community evidence. However, integration may also occur through conventional GIS and planning-support systems without AI. Algorithmic outputs are therefore treated as decision-support evidence, not planning decisions; public-interest judgement, local knowledge, statutory responsibility and professional accountability remain indispensable (Son et al., 2023; Yigitcanlar et al., 2020).

Within the reviewed corpus, direct evidence is stronger for urban-growth analysis and housing-location planning than for subsequent architectural neighbourhood design. Architectural implications are therefore treated as a reasoned design translation of the spatial evidence rather than as equally extensive GeoAI-specific empirical evidence. Suitability models may identify favourable locations, but neighbourhood performance also depends on density, circulation, drainage, public space, housing form, infrastructure and accessibility; conversely, architectural quality can be undermined when location and infrastructure sequencing are ignored (Ayoola et al., 2023; Davern et al., 2017; Parry et al., 2018; Schirmer et al., 2014).

For analytical clarity, Architecture and Urban and Regional Planning are treated as the two principal professional lenses. This does not imply a two-profession delivery process: implementation may additionally require surveying/GIS, civil and infrastructure engineering, environmental, transport, cost, community-engagement and data/AI expertise according to project scope. In Nigeria, architectural practice is regulated by the Architects Registration Council of Nigeria (ARCON) under the Architects (Registration, Etc.) Act, Cap. A19, Laws of the Federation of Nigeria 2004, while town-planning practice is regulated by the Town Planners Registration Council of Nigeria (TOPREC) under the Town Planners (Registration, Etc.) Act, Cap. T7, Laws of the Federation of Nigeria 2004 (Architects (Registration, Etc.) Act, 2004; Town Planners (Registration, Etc.) Act, 2004). The framework therefore allocates professional judgement within the applicable statutory and disciplinary responsibilities without subordinating either profession to technological systems.

Three questions guide the review: (1) which GeoAI and complementary geospatial methods can support growth monitoring and housing-location assessment in Nigerian secondary cities; (2) how should planning evidence be interpreted and translated into architectural neighbourhood decisions; and (3) which validation, governance, participation and implementation safeguards are required for responsible adoption? The article develops an integrated architecture-planning decision framework in which geospatial evidence informs lawful growth choices and is subsequently translated into liveable neighbourhood form.

Review Design And Analytical Procedure

A critical structured narrative review was adopted because the research problem crosses urban growth management, GeoAI, remote sensing, housing-location suitability, infrastructure planning, architecture and AI governance. Narrative synthesis is suitable for heterogeneous evidence that cannot be meaningfully pooled, while explicit search, selection, coding and appraisal procedures improve transparency (Grant & Booth, 2009; Green et al., 2006; Snyder, 2019).

Google Scholar was used for broad discovery, supplemented by targeted searches of relevant Scopus-indexed journals and major publisher platforms, including ScienceDirect, Taylor & Francis Online, SpringerLink, MDPI and SAGE Journals. The search was updated on 30 July 2026. The analytical publication window was bounded at 2010-2025 to maintain a complete calendar-year corpus; the 2026 update was used to check the stability and currency of the synthesis rather than add partial-year analytical studies. Search concepts were organised into thematic blocks covering GeoAI/AI, GIS and remote sensing, urban-growth modelling, housing-location suitability, planning-support systems, infrastructure sequencing, urban sprawl, Nigerian/African urbanisation, secondary cities and responsible-AI governance. A reproducible operationalisation of these concepts is provided in Supplementary Table S1.

Table 1: Review evidence allocation

Review theme	Dominant evidence role	Representative analytical evidence	No.
Urban growth management	Urban-expansion patterns, scenarios and growth consequences	Angel et al. (2011); Chen et al. (2020); Güneralp et al. (2017); Oyalowo (2022); Seto et al. (2012); Shao et al. (2021)	6
Planning support and GeoAI	Planning-support science; urban AI/ML; GeoAI decision support	Casali et al. (2022); Chaturvedi & de Vries (2021); Drici & Carpio-Pinedo (2025); Geertman & Stillwell (2020); Mortaheb & Jankowski (2023); Othengrafen et al. (2025); Oyeku et al. (2024); Pelzer et al. (2014); Pettit et al. (2018); Sanchez et al. (2023)	10
Remote sensing and GIS	Change detection, spatial simulation and LULC analysis	Ahmed & Ahmed (2012); Alegbeleye et al. (2024); Balogun et al. (2011); Blaschke (2010); Jokar Arsanjani et al. (2013); Koko et al. (2021); Liang et al. (2021); Ologunde et al. (2025); Santé et al. (2010)	9
Housing-location suitability	Location choice, accessibility, suitability and affordability	Ayoola et al. (2023); Borth et al. (2024); Huang et al. (2019); Marwal & Silva (2023); Schirmer et al. (2014)	5
Infrastructure sequencing	Infrastructure, service access, flood resilience and spatial MCDA	Alves et al. (2020); Coutinho-Rodrigues et al. (2011); Davern et al. (2017); Iamtrakul et al. (2024); Masoumi & van Genderen (2024); Parry et al. (2018)	6
AI governance and ethics	Urban-AI governance, ethics, accountability and human oversight	Caprotti et al. (2024); Floridi et al. (2018); Sanchez et al. (2025); Son et al. (2023); Yigitcanlar et al. (2020)	5
Nigerian/African urbanisation	Local/African urbanisation, land-cover change and planning context	Ajagbe et al. (2021); Aliyu & Amadu (2017); Cobbinah et al. (2015); Ogunleye & Owoeye (2015); Olofin & Oluwadare (2022)	5
Total			**46**

Note: Each analytical article is counted once under a dominant theme. Method class is treated separately in Table 2 so that conventional GIS/remote sensing, spatial simulation, multicriteria analysis, planning-support systems and AI/ML-based GeoAI are not conflated.

Inclusion required substantial relevance to urban expansion, AI/geospatial planning, housing location, infrastructure planning, Nigerian or African urbanisation, planning-support systems or AI governance. Foundational studies were retained where necessary for urban-expansion modelling or planning-support theory.

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Duplicates, opinion pieces, promotional material, non-verifiable online sources, weakly related papers and purely technical AI studies without spatial-planning relevance were excluded. Screening proceeded through title/abstract relevance assessment followed by full-text review. The final analytical corpus comprised 46 peer-reviewed articles. Intermediate retrieval, duplicate-removal and exclusion counts were not preserved in the review record used for this manuscript and are therefore not retrospectively reconstructed.

For counting purposes, each article was assigned to one dominant review theme to prevent double counting; multidisciplinary contributions were additionally coded across secondary themes during synthesis. For each analytical article, extraction covered author/year, geographic context, urban scale, study/evidence type, data or analytical basis, method class, principal contribution, limitations and transferability to Nigerian secondary cities. Sources were qualitatively appraised for methodological transparency, appropriateness of data and spatial scale, validation procedure, uncertainty reporting, contextual relevance, governance/equity treatment and transferability. This appraisal informed evidential weighting but was not converted into a numerical risk-of-bias score. Methodological references and institutional, statutory and policy documents were used separately for review design, urban policy, climate context, AI governance and data protection. The review was not designed or reported as a PRISMA-compliant systematic review and does not undertake meta-analysis.

Table 2: Characteristics and critical appraisal of the 46-study analytical corpus

Study	Context/scale	Method class	Principal contribution to this review	Critical limitation/transferability
Angel et al. (2011).	Global urban expansion	Urban-growth estimation/ projection	Establishes dimensions and trajectories of urban expansion relevant to growth management.	Global aggregate evidence; does not establish local Nigerian suitability or implementation conditions.
Chen et al. (2020).	Global future urban land expansion	Scenario-based spatial projection	Demonstrates how urban land expansion can be projected under socioeconomic scenarios.	Scenario assumptions and global scale limit direct transfer to secondary-city parcel decisions.
Güneralp et al. (2017).	Global urban density and energy scenarios	Urban-form scenario modelling	Links density trajectories with long-term building-energy implications.	Energy implications are macro-scale and not evidence of local housing-site or architectural performance.
Oyalowo (2022)	Lagos, Nigeria	Urban expansion/ planning-housing analysis	Provides Nigerian evidence on land, planning and housing implications of expansion.	Metropolitan Lagos differs institutionally and spatially from smaller secondary cities.
Seto et al. (2012).	Global urban expansion	Forecasting / environmental impact analysis	Shows broader ecological consequences of continued urban expansion.	Not a housing-suitability or GeoAI design study; transfer is conceptual.
Shao et al. (2021).	Urban-sprawl context	Remote sensing plus social-media analysis	Illustrates integration of spatial and volunteered/digital data for sprawl analysis.	Data representativeness and context-specific calibration limit direct Nigerian transfer.
Casali et al. (2022).	Urban areas; international review	ML spatial-analysis scoping review	Maps machine-learning applications, data types and methodological issues in urban spatial analysis.	Secondary evidence; application quality depends on local data and validation.
Chaturvedi & de Vries (2021).	Urban land-use planning; review	Machine-learning review	Clarifies AI/ML roles in land-use planning and associated methodological considerations.	Review evidence does not validate specific Nigerian planning workflows.

Drici & Carpio-Pinedo (2025).	Urban land-use mix; review	AI systematic review	Synthesises recent AI applications for land-use mix analysis.	Recent, heterogeneous evidence; limited direct evidence for Nigerian secondary cities.
Geertman & Stillwell (2020).	Planning-support science	Planning-support conceptual/methodological synthesis	Supports use of decision-support tools to compare alternatives and inform professional deliberation.	Planning-support principles are transferable, but institutional embedding must be locally tested.
Mortaheb & Jankowski (2023).	Smart city/planning	GeoAI conceptual review	Frames GeoAI as decision support within data-rich city planning.	Conceptual rather than outcome-validation evidence; assumes data capacity is often absent locally.
Othengrafen et al. (2025).	Urban planning phases	AI-in-planning analysis	Shows AI uses differ across planning phases and require professional integration.	Institutional and legal conditions vary; benefits are not automatically transferable.
Oyeku et al. (2024)	Spatial planning practice	Planning-support implementation study	Shows planning-support systems must be embedded in practice rather than treated as standalone tools.	Practice context differs; implementation lessons require local institutional adaptation.
Pelzer et al. (2014).	Planning practice	Practitioner evaluation of planning-support systems	Provides evidence that perceived value depends on usability, communication and decision context.	Not GeoAI-specific and predates current AI methods; still useful for adoption logic.
Pettit et al. (2018).	Smart-city planning	Planning-support systems synthesis	Supports interoperable data, dashboards and decision-support integration.	Smart-city maturity assumptions may exceed data/institutional capacity of secondary cities.
Sanchez et al. (2023).	Urban planning; international	AI-planning review/prospects	Identifies potential AI roles while retaining human planning judgement.	Prospective evidence; does not establish realised performance in Nigerian housing growth.
Ahmed & Ahmed (2012).	Dhaka, Bangladesh	Remote sensing / urban-growth modelling	Demonstrates multi-temporal land-cover growth modelling.	Different urban morphology and governance; model calibration is location-specific.
Alegbeleye et al. (2024).	Nigeria	Systematic review of LULC analysis	Provides national overview of land-use/land-cover methods and evidence.	Review-level evidence; heterogeneity limits city-specific conclusions.
Balogun et al. (2011).	Akure, Nigeria	Remote sensing and GIS change detection	Provides direct Nigerian secondary-city evidence of urban expansion and land-use change.	Historical retrospective evidence; does not establish current suitability or preferred future growth.
Blaschke (2010)	Remote-sensing literature	Object-based image-analysis review	Establishes methodological basis for image-based land-cover classification.	Methodological evidence; classification outputs require local accuracy assessment.
Jokar Arsanjani et al. (2013).	Urban expansion case study	Logistic regression + Markov chain + cellular automata	Shows integration of statistical and spatial simulation for expansion modelling.	Spatial simulation is not necessarily AI; transfer requires re-estimation with local data.
Koko et al. (2021).	Lagos, Nigeria	Remote sensing and GIS scenario analysis	Links land-cover growth scenarios with flood-mitigation concerns in Nigeria.	Metropolitan context and flood model assumptions may not transfer to secondary cities.
Liang et al. (2021).	Wuhan, China	PLUS land-use simulation	Demonstrates patch-generating spatial simulation and driver analysis.	Model is context-specific; sophisticated data requirements may constrain local application.

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Ologunde et al. (2025).	Nigeria	LULC case analysis	Provides recent Nigerian evidence of continuing land-use and land-cover change.	National/case evidence does not establish site-level planning priorities.
Santé et al. (2010).	Urban-process literature	Cellular-automata review	Clarifies strengths and limitations of CA models for urban processes.	Foundational and pre-GeoAI; simulation is not synonymous with AI.
Ayoola et al. (2023).	Residential-location choice	Empirical location-choice analysis	Highlights transportation, facilities and environmental attributes in residential location decisions.	Location-choice evidence does not alone define statutory suitability or neighbourhood design quality.
Borth et al. (2024).	Location-efficiency literature	Narrative review	Clarifies location efficiency across scales and supports access/service criteria.	Conceptual synthesis; operational thresholds require local definition.
Huang et al. (2019).	Beijing, China	Remote sensing + social sensing suitability analysis	Demonstrates multi-source urban residential land-suitability analysis.	Data availability, weights and urban context differ substantially from Nigerian secondary cities.
Marwal & Silva (2023).	Urban residential affordability/location	Agent-based modelling	Shows interactions between affordability and residential location choice.	Agent assumptions and market conditions are context-dependent.
Schirmer et al. (2014).	Residential-location literature	Literature review/model synthesis	Clarifies importance of location variables in residential choice models.	Review-level evidence; not a validated housing-growth suitability model.
Alves et al. (2020).	Urban flood mitigation	Multi-criteria trade-off analysis	Shows infrastructure choices involve trade-offs among environmental and service benefits.	Infrastructure design is specialist work; findings do not specify Nigerian project thresholds.
Coutinho-Rodrigues et al. (2011).	Urban infrastructure planning	GIS-based multicriteria decision support	Demonstrates transparent GIS/MCDA for infrastructure planning.	Weights and criteria are normative and must be sensitivity-tested locally.
Davern et al. (2017).	Social infrastructure/ health	Spatial accessibility measures	Supports service-access and social-infrastructure indicators for neighbourhood assessment.	Indicator thresholds and service standards require local calibration.
Iamtrakul et al. (2024).	Urban facility accessibility	Spatial accessibility analysis	Supports assessment of spatial disparities in facility access.	Non-Nigerian context; accessibility definitions and transport modes require localisation.
Masoumi & van Genderen (2024).	Smart cities / land-use management	AI and geospatial review	Provides recent synthesis of AI for urban land-use management.	Broad review; may overrepresent data-rich smart-city contexts.
Parry et al. (2018).	Indian urban centres	GIS-AHP multicriteria suitability	Demonstrates spatial suitability analysis using explicit criteria and weighting.	AHP weights are judgement-dependent; local criteria and sensitivity analysis are essential.
Caprotti et al. (2024).	Urban AI research	Critical conceptual analysis	Highlights power, governance and research implications of urban AI.	Conceptual evidence; does not prescribe operational planning controls.
Floridi et al. (2018).	General AI governance	Ethical framework	Provides fairness, accountability, transparency and human-centred principles.	General framework requires translation into planning-specific procedures.
Sanchez et al. (2025).	Urban planning	AI ethics analysis	Directly identifies ethical concerns for AI-supported planning decisions.	Primarily governance-focused; does not validate technical planning performance.

Son et al. (2023).	Algorithmic urban planning; review	Systematic review	Synthesises algorithmic planning applications, opportunities and risks.	Heterogeneous studies and smart-city contexts constrain direct local inference.
Yigitcanlar et al. (2020).	Smart cities; review	Systematic review of AI contributions/risks	Balances AI opportunities with governance, risk and implementation concerns.	Broad smart-city literature; secondary-city Nigerian conditions remain underrepresented.
Ajagbe et al. (2021).	Ado-Ekiti, Nigeria	Remote sensing LULC change analysis	Provides direct local evidence of historical land-use/land-cover change.	Retrospective LULC evidence does not establish current infrastructure capacity or site suitability.
Aliyu & Amadu (2017).	Nigeria	Urbanisation/public-health review	Provides Nigerian context on rapid urbanisation and infrastructure/service challenges.	Broad national review; not GeoAI-specific or secondary-city comparative evidence.
Cobbinah et al. (2015).	Africa	Urbanisation/sustainability analysis	Frames infrastructure, informality and sustainable-development pressures across African cities.	Regional generalisation masks large institutional and city-scale differences.
Ogunleye & Owoeye (2015)	Ado-Ekiti, Nigeria	Land-use change study around EKSU	Shows institution-related development and local land-use transformation.	Area-specific historical evidence; no current suitability ranking or infrastructure audit.
Olofin & Oluwadare (2022).	Ado-Ekiti, Nigeria	Settlement growth and land-surface-temperature analysis	Links local settlement growth with land-surface-temperature change.	Environmental association does not establish causal design performance or preferred growth locations.

Note: The table distinguishes evidence roles and methodological classes without assigning a numerical risk-of-bias score. Transferability judgements are qualitative and reflect the review's emphasis on data provenance, spatial scale, validation, institutional context and relevance to Nigerian secondary-city housing growth.

Conceptual Foundations

Growth-management literature addresses the location, pace, form and infrastructure consequences of urban expansion through planning instruments such as serviced-land provision, compact-growth strategies, environmental protection and phased infrastructure investment (Coutinho-Rodrigues et al., 2011; United Nations Human Settlements Programme [UN-Habitat], 2015; United Nations, 2017). In secondary cities, this shifts the analytical focus from growth prevention to the relationship among accessibility, infrastructure capacity, environmental conditions and sustainable settlement form.

Housing-location research identifies accessibility, transport, public facilities, environmental quality, affordability and neighbourhood conditions as important influences on residential location choice and location efficiency (Ayoola et al., 2023; Borth et al., 2024; Marwal & Silva, 2023; Schirmer et al., 2014). This evidence indicates that apparently inexpensive peripheral land may generate wider affordability and service-access burdens through longer travel and additional infrastructure requirements.

Planning-support systems add value when they help professionals compare alternatives, expose assumptions and communicate trade-offs rather than automate approval. GeoAI can strengthen selected functions by identifying patterns or supporting predictions that are difficult to generate manually, but model outputs remain contingent on data quality, spatial scale, variable selection, validation and institutional use (Casali et al., 2022; Mortaheb & Jankowski, 2023; Othengrafen et al., 2025; Pettit et al., 2018).

Responsible use requires human oversight and transparent governance. International AI frameworks emphasise fairness, transparency, accountability and human-centred decision-making, while Nigerian data-protection and AI-policy instruments provide the relevant national governance context (Federal Ministry of Communications, Innovation and Digital Economy, 2025; Nigeria Data Protection Act, 2023; Organisation for Economic Co-operation and Development [OECD], 2024; United Nations Educational, Scientific and Cultural Organization [UNESCO], 2021).

Urban Expansion In Nigerian Secondary Cities

Urban expansion affects land consumption, infrastructure demand, ecosystem conditions and long-term exposure to environmental risk. In this review, these broader consequences are used to justify anticipatory housing-growth planning rather than to imply that the reviewed GeoAI studies directly quantify all climate or energy outcomes (Angel et al., 2011; Chen et al., 2020; Güneralp et al., 2017; Intergovernmental Panel on Climate Change, 2022; Seto et al., 2012; UN-Habitat, 2024).

African urbanisation research associates rapid growth with land informality, infrastructure deficits and uneven planning capacity, while Nigerian metropolitan evidence shows how expansion can cross administrative boundaries where land-market pressures and enforcement are weak (Aliyu & Amadu, 2017; Cobbinah et al., 2015; Oyalowo, 2022). These patterns establish a relevant comparative context for secondary cities, but the evidence does not support assuming identical pressures, demographic trajectories or institutional capacity across locations.

Remote-sensing studies of Ado-Ekiti and Akure document historical settlement and land-cover change, providing local evidence of expansion (Ajagbe et al., 2021; Balogun et al., 2011; Ogunleye & Owoeye, 2015; Olofin & Oluwadare, 2022). Broader Nigerian evidence confirms continuing land-use and land-cover change across urbanising landscapes (Alegbeleye et al., 2024; Ologunde et al., 2025). These studies do not by themselves establish current housing-site suitability, infrastructure capacity or preferred future growth directions; those questions require contemporary, decision-specific evidence.

Geospatial And GeoAI Methods For Growth Monitoring And Housing-Site Suitability

Remote sensing and GIS support change detection and spatial representation; cellular automata and other spatial simulation methods estimate possible growth patterns; and AI/ML methods may support classification, prediction, clustering or pattern recognition. These approaches are complementary but methodologically distinct (Ahmed & Ahmed, 2012; Blaschke, 2010; Casali et al., 2022; Chaturvedi & de Vries, 2021; Jokar Arsanjani et al., 2013; Liang et al., 2021; Santé et al., 2010). Their planning value depends on a defined decision problem and on distinguishing descriptive or predictive outputs from preferred development choices.

Housing-site suitability is an evaluative decision-support task rather than simply an extension of prediction. It combines explicit planning criteria - such as accessibility, environmental constraints, infrastructure capacity, service proximity, land-use compatibility, tenure and location-related cost - through transparent weighting or decision rules (Coutinho-Rodrigues et al., 2011; Huang et al., 2019; Parry et al., 2018). Social and location-efficiency evidence adds travel time, affordability and service proximity to the assessment (Ayoola et al., 2023; Borth et al., 2024; Davern et al., 2017; Iamtrakul et al., 2024; Marwal & Silva, 2023).

Growth prediction and housing-site suitability therefore answer different questions. Predictive and classification models should report model-appropriate accuracy and uncertainty measures, while suitability models should disclose criteria, weights, normalisation procedures and sensitivity tests. Both require field verification and stakeholder/professional review before consequential use (Blaschke, 2010; Casali et al., 2022; Chaturvedi & de Vries, 2021; Pettit et al., 2018).

Table 3: Integrated decision tests for geospatial and GeoAI-supported housing growth

Decision question	Geospatial / GeoAI evidence	Urban & Regional Planning judgement	Architecture response
Where is growth occurring?	Remote-sensing change detection; building footprints; road and land-use trajectories; spatial	Distinguish observed/predicted pressure from preferred	Assess implications for settlement form, density, access, service relationships and neighbourhood structure.

	simulation where appropriate.	growth; identify corridors needing policy attention.	
Which land is suitable for housing?	Network accessibility; terrain/slope; flood and environmental constraints; infrastructure/service proximity; land-use compatibility; tenure/statutory constraints; location-related cost.	Apply land-use policy, infrastructure capacity, environmental safeguards and public-interest criteria; document criteria and weights.	Translate preferred land into density, orientation, housing mix, street/block structure, public realm, climate response, drainage and service-aware design.
What infrastructure should be sequenced first?	Service-gap mapping; growth forecasts; network/terrain analysis; facility accessibility.	Phase infrastructure with approved growth areas; reserve critical rights-of-way; verify capacity with specialists.	Coordinate streets, public space, access, drainage and service corridors with housing phases.
Which land should be protected or conditioned?	Flood/drainage, erosion, heat exposure and ecological constraints using locally validated data.	Restrict or condition development and protect environmental systems/corridors.	Redesign density, open space and housing form around protected systems and hazard constraints.
Is the preferred option liveable and implementable?	Travel time, service proximity, demand, community feedback, environmental constraints and spatial risk.	Test accessibility, equity, participation, infrastructure fit and statutory compliance.	Test walkability, public realm, housing adaptability, service integration and neighbourhood identity; coordinate specialist feasibility checks.

Source. Authors' synthesis based on Alves et al. (2020), Ayoola et al. (2023), Borth et al. (2024), Coutinho-Rodrigues et al. (2011), Davern et al. (2017), Huang et al. (2019), Marwal and Silva (2023), Parry et al. (2018), and Nigerian urban-growth evidence (Ajagbe et al., 2021; Balogun et al., 2011; Ogunleye & Owoeye, 2015; Olofin & Oluwadare, 2022).

Note: The criteria constitute an authors' synthesis for structured decision support rather than a validated universal suitability model. Variables, weights, thresholds and spatial resolutions should be locally justified and subjected to sensitivity analysis, field verification, statutory review and stakeholder scrutiny before implementation.

Planning Translation And Infrastructure Sequencing

Infrastructure and accessibility literature shows that roads, drainage, water, sanitation, electricity and social facilities shape settlement efficiency and everyday access, while uncoordinated layouts can create retrofitting costs and service discontinuities (Aliyu & Amadu, 2017; Ajagbe et al., 2021; Davern et al., 2017; Olofin & Oluwadare, 2022). Infrastructure sequencing is therefore treated as an early planning and design requirement rather than a post-layout consideration. Detailed engineering feasibility, capacity and design remain within the competence of the relevant infrastructure specialists.

Planning-support research supports linking growth forecasts with infrastructure capacity, terrain, environmental risk, accessibility and projected population before major housing layouts are committed (Coutinho-Rodrigues et al., 2011; Geertman & Stillwell, 2020; Parry et al., 2018; Pelzer et al., 2014). Green-blue-grey infrastructure studies further show that drainage and flood-risk decisions involve trade-offs among multiple environmental and service benefits (Alves et al., 2020; Koko et al., 2021).

Urban and Regional Planning therefore defines the spatial decision problem, interprets land-use suitability, coordinates infrastructure sequencing and development-control requirements, organises participation and distinguishes predicted growth from preferred growth. Infrastructure capacity and engineering feasibility require specialist verification before implementation. This separation preserves the public-interest and statutory role of planning while recognising the technical responsibilities of other built-environment disciplines.

Architectural Translation From Suitable Land To Liveable Neighbourhood Form

Housing-location and liveability evidence indicates that a suitable site does not by itself constitute a liveable neighbourhood. Accessibility, affordability and neighbourhood conditions remain dependent on how selected land is translated into density, circulation, housing mix, public space, communal facilities and service relationships (Ayoola et al., 2023; Borth et al., 2024; Davern et al., 2017; Iamtrakul et al., 2024; Marwal & Silva, 2023; Schirmer et al., 2014). Architectural judgement therefore operates as the design translation of the preferred planning option.

Architecture translates the preferred planning option into testable neighbourhood-design alternatives addressing density, housing mix, block and street structure, orientation, public realm, communal facilities, access and service relationships, while specialist inputs verify drainage, utilities, structural, environmental and infrastructure feasibility. Infrastructure and spatial-planning evidence supports protecting drainage corridors, coordinating access and utility routes, and relating housing form to public-space and service networks (Alves et al., 2020; Davern et al., 2017; Parry et al., 2018).

Geospatial evidence can support architectural exploration by making site constraints, access patterns, hazards and service relationships explicit, while GeoAI may augment prediction or pattern recognition. Neither determines neighbourhood form independently of architectural judgement, planning review and community validation where choices affect social inclusion, mobility, land-use trade-offs and everyday access (Sanchez et al., 2025; UNESCO, 2021). The architectural contribution in this review is therefore a reasoned translation of spatial evidence into buildable alternatives, not a claim that GeoAI autonomously generates or validates design quality.

Governance, Participation And GeoAI Risks

GeoAI-supported planning carries data, governance and distributive risks where datasets are incomplete, outdated, spatially biased or insufficiently representative of informal settlements and vulnerable populations. Ranked outputs can obscure normative choices about criteria and weights, while mobility, property or vulnerability data may create privacy concerns. Urban-AI scholarship therefore stresses power, accountability and the politics of data as well as technical capability (Caprotti et al., 2024; Floridi et al., 2018; Yigitcanlar et al., 2020).

International guidance emphasises trustworthy AI, transparency, fairness, accountability, human oversight and protection of rights, while formal AI-risk guidance further supports systematic identification, evaluation and treatment of AI-related risks (International Organization for Standardization [ISO], 2023; OECD, 2024; UNESCO, 2021). In Nigeria, where GeoAI and planning workflows process personal data, such processing is subject to the Nigeria Data Protection Act, 2023. The National Artificial Intelligence Strategy provides additional policy direction for responsible, ethical and inclusive AI development and deployment (Federal Ministry of Communications, Innovation and Digital Economy, 2025; Nigeria Data Protection Act, 2023).

For consequential GeoAI-supported decisions, governance documentation should record data provenance and dates; spatial resolution; represented and excluded populations or areas; model purpose; variables, criteria and weights; uncertainty and validation results; professional modifications; excluded alternatives; privacy safeguards; responsible reviewers; and available mechanisms for review or challenge. Community verification is especially important where official data omit informal paths, transport routes, tenure relationships or local hazards (OECD, 2024; Sanchez et al., 2025; UNESCO, 2021).

Integrated Architecture-Planning Decision Framework

The proposed framework synthesises the reviewed evidence into six linked stages: verified urban and community evidence; geospatial/GeoAI analysis; urban and regional planning interpretation; architectural neighbourhood-design translation; joint professional, statutory and community validation; and implementation, monitoring and post-occupancy learning. An explicit feedback loop returns measured outcomes and implementation experience to the evidence, planning and design stages. Data governance, model transparency and accountability operate across the entire sequence rather than as a final-stage check. This structure separates analytical prediction from professional judgement because planning-support and responsible-AI literature treats model outputs as inputs to deliberative and accountable decisions rather than automatic approvals (Geertman & Stillwell, 2020; Othengrafen et al., 2025; Sanchez et al., 2025; UNESCO, 2021).

Table 4: Complementary responsibilities of Urban and Regional Planning and Architecture

Professional lens	Core responsibility	Geospatial / GeoAI-supported contribution
Urban & Regional Planning	Spatial policy, land use, housing-location suitability, infrastructure sequencing, participation and development control.	Defines planning questions; validates spatial evidence; compares growth scenarios; interprets preferred options within statutory, development-control and implementation processes.
Architecture	Housing and neighbourhood form, climate response, access, public realm, spatial quality, service-aware design and resident experience.	Translates preferred planning options into density, housing mix, circulation, public space, climate response and coordinated neighbourhood-design alternatives.

Source. Authors' synthesis based on Nigerian professional-regulatory frameworks, planning-support and AI-planning literature, urban and territorial planning guidance, and responsible-AI governance (Architects (Registration, Etc.) Act, 2004; Geertman & Stillwell, 2020; Othengrafen et al., 2025; OECD, 2024; Sanchez et al., 2023, 2025; Town Planners (Registration, Etc.) Act, 2004; UN-Habitat, 2015; UNESCO, 2021).

Note: The table identifies the two principal professional lenses examined in this review rather than the complete project team. Delivery may additionally require GIS/surveying, transport, civil/infrastructure, environmental, cost, community-engagement and data/AI expertise according to the decision context.

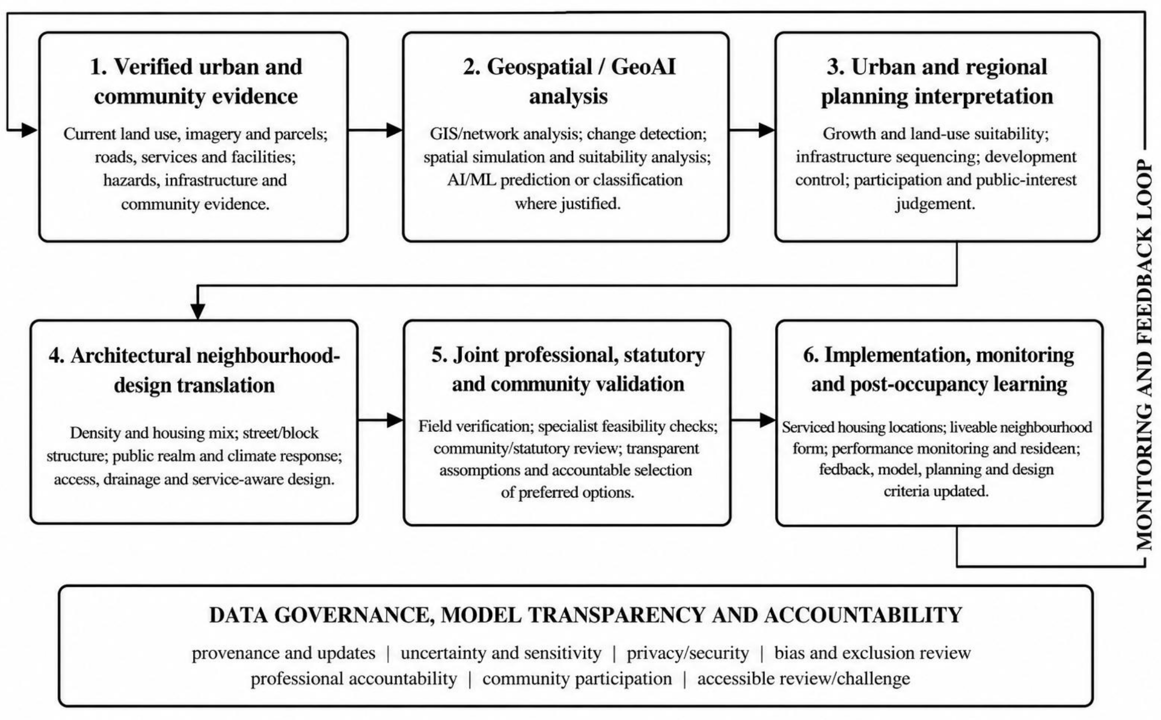

Figure 1: Proposed iterative geospatial and GeoAI-assisted architecture-planning framework for responsible housing growth in Nigerian secondary cities.

Source. Authors' conceptual synthesis based on Ayoola et al. (2023), Borth et al. (2024), Casali et al. (2022), Chaturvedi and de Vries (2021), Mortaheb and Jankowski (2023), Othengrafen et al. (2025), Parry et al. (2018), OECD (2024), UNESCO (2021), ISO (2023), the Nigeria Data Protection Act (2023), the Architects (Registration, Etc.) Act (2004), the Town Planners (Registration, Etc.) Act (2004), and Nigerian urban-growth evidence (Ajagbe et al., 2021; Balogun et al., 2011; Ogunleye & Owoeye, 2015; Olofin & Oluwadare, 2022).

Illustrative Application to Ado-Ekiti

Ado-Ekiti is used as an illustrative setting because local studies document settlement expansion, land-cover change and institution-related development, while national urban analysis highlights continuing questions of service access, infrastructure and mobility (Ajagbe et al., 2021; Ogunleye & Owoeye, 2015; Olofin & Oluwadare, 2022; World Bank, 2025). The paper does not infer current site-suitability conditions for named corridors or estates from these sources.

A future Ado-Ekiti pilot should combine current satellite imagery with verified cadastral, road, facility, drainage/flood, terrain, building, utility and planning-approval data and community-validated local knowledge. Because these datasets may vary in completeness and currency, each source should be documented for date, scale, accuracy, ownership and known omissions before modelling. These data categories reflect variables used across growth monitoring, housing-location suitability, infrastructure and participatory planning literature (Casali et al., 2022; Coutinho-Rodrigues et al., 2011; Parry et al., 2018; Pettit et al., 2018).

Candidate growth areas could be compared using explicitly defined and sensitivity-tested criteria for accessibility, environmental risk, land-use compatibility, infrastructure capacity, serviceability, statutory feasibility and neighbourhood-design potential. No site-ranking claim should be made until current local data and field verification are completed. In the proposed workflow, geospatial/GeoAI analysis identifies candidate patterns, Urban and Regional Planning interprets growth and statutory implications, Architecture develops neighbourhood and public-realm alternatives, and professional, community and statutory review validates the preferred option (Geertman & Stillwell, 2020; Othengrafen et al., 2025; Pelzer et al., 2014).

DISCUSSION AND IMPLICATIONS

Evidence consensus, asymmetry and trade-offs

Three conclusions recur across the reviewed evidence. First, geospatial methods can make urban change, service deficits and environmental constraints more visible, while GeoAI-specific methods may add prediction or classification; neither determines a preferred development pathway. Second, housing-site suitability is multidimensional: accessibility and hazard must be interpreted alongside infrastructure, tenure, neighbourhood form and public-interest criteria. Third, digital decision support is more consistently supported when embedded in professional and participatory processes rather than treated as an automated ranking exercise (Casali et al., 2022; Geertman & Stillwell, 2020; Othengrafen et al., 2025; Oyeku et al., 2024; Parry et al., 2018).

The evidence base is asymmetric. Direct empirical evidence is comparatively strong for land-use change, growth modelling, accessibility and suitability analysis, but weaker for the subsequent architectural translation of GeoAI outputs into completed neighbourhoods. Consequently, the architectural propositions in this review are framed as testable design implications of spatial evidence rather than as demonstrated causal effects of GeoAI on neighbourhood quality.

The synthesis also reveals important trade-offs. A highly accessible parcel may have flood, tenure or infrastructure constraints; compact growth may reduce infrastructure-extension costs while increasing pressure on drainage, services or public space; high model accuracy does not ensure socially legitimate suitability criteria; and additional predictive sophistication may increase data, maintenance and governance burdens. Models may favour parcels represented well in formal datasets while undervaluing informal routes, tenure arrangements, seasonal drainage conditions, community priorities or implementation constraints. These tensions favour transparent multi-criteria and participatory evaluation rather than a single composite suitability score.

Practice and policy implications

For practice, secondary-city authorities should prioritise a governed geospatial information base covering land use, parcels, roads, buildings, utilities, public facilities, environmental constraints and approved development, with documented custodianship, update cycles and metadata. Advanced GeoAI should follow rather than precede reliable foundational data. For major housing schemes, combining documented planning justification with an architectural neighbourhood response enables accessibility, drainage, service integration, climate response and public-realm quality to be assessed before approval or public investment (Geertman & Stillwell, 2020; Parry et al., 2018; Pettit et al., 2018; UN-Habitat, 2015).

Architectural use of geospatial evidence is strongest when suitability outputs are treated as evidence for comparing density, housing mix, street and public-space structure, environmental response, access and site-service relationships rather than as design solutions. Planning-support and responsible-AI literature likewise supports documenting assumptions, retaining professional review and preserving consultation or appeal mechanisms around consequential spatial decisions (Othengrafen et al., 2025; Sanchez et al., 2025; UNESCO, 2021).

Implementation therefore requires capacity not only in software operation but also in spatial-data quality, model interpretation, uncertainty and sensitivity analysis, statutory planning, architectural design translation, participatory methods and responsible-AI governance. A capability-based pathway is preferable to fixed implementation durations because institutional capacity, data readiness, statutory procedures and project scale vary between cities.

Table 5: Capability-based implementation pathway for geospatial and GeoAI-supported housing-growth planning and neighbourhood design

Capability phase	Urban & Regional Planning output	Architecture output	Safeguard/performance evidence
Phase 1 - Readiness and problem definition	Define pilot boundary, planning questions, data custodianship, statutory context and decision criteria.	Prepare neighbourhood-performance brief, design criteria and site-information needs.	Approved pilot protocol; data inventory/quality report; roles and governance documented.
Phase 2 - Spatial baseline and field validation	Prepare growth atlas, service-gap, accessibility, risk and infrastructure baseline; verify with field/community evidence.	Undertake site reconnaissance and develop preliminary access, public-realm and neighbourhood options.	Data gaps and local omissions documented; field/community validation completed.
Phase 3 - Suitability/scenario analysis and design testing	Develop transparent suitability and infrastructure-sequencing scenarios; distinguish predicted from preferred growth.	Compare density, housing mix, climate response, drainage/service coordination and public realm.	Criteria, weights and assumptions documented; sensitivity/uncertainty assessed; specialist checks recorded.
Phase 4 - Statutory and participatory decision	Select preferred growth option; integrate development-control conditions and infrastructure commitments.	Prepare coordinated neighbourhood proposal and design brief for the preferred planning option.	Public/community review, statutory decision, professional sign-off and auditable rationale.
Phase 5 - Implementation monitoring and feedback	Monitor land-use, infrastructure and service-access outcomes and update spatial evidence.	Undertake post-occupancy spatial, environmental and resident evaluation; refine design criteria.	Updated models, liveability indicators and planning/design criteria; lessons returned to Phases 1-3.

Source. Proposed implementation sequence synthesised from Geertman and Stillwell (2020), Othengrafen et al. (2025), Oyeku et al. (2024), Parry et al. (2018), Pelzer et al. (2014), Sanchez et al. (2025), OECD (2024), UNESCO (2021), the Nigeria Data Protection Act (2023), the Architects (Registration, Etc.) Act (2004), the

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Town Planners (Registration, Etc.) Act (2004), and Nigerian urban-growth evidence. The sequence is a testable framework rather than a validated protocol.

Table 6: Candidate monitoring indicators for GeoAI-supported housing-growth pilots

Outcome domain	Candidate indicator / operational definition	Primary data source	Spatial/social scale	Interpretation/limitation
Land-use efficiency	Share of planned growth occurring within approved/serviced areas; land consumption per added dwelling or population unit.	Planning approvals, cadastral/land-use records, remote sensing	Parcel/ neighbourhood/ city	Interpret with tenure and development-market conditions; compactness alone is not liveability.
Service accessibility	Median travel time or network distance to schools, health facilities, markets and public transport; % population within locally defined thresholds.	GIS/network analysis, facility registers, household/mobility surveys	Neighbourhood/ population group	Thresholds should reflect local modes, informal transport and walking conditions.
Infrastructure coverage	% occupied plots/dwellings with functional road access, drainage, water, sanitation and electricity; service interruptions where relevant.	Utility/infrastructure records, field audits, resident surveys	Neighbourhood/ block	Coverage should distinguish presence from reliability and capacity.
Environmental exposure	% housing or land area intersecting locally validated flood, erosion, heat or ecological constraints; change in exposure after intervention.	Hazard maps, remote sensing, field verification	Parcel/block/ neighbourhood	Hazard data date, spatial resolution and uncertainty should be reported.
Housing-transport accessibility	Combined housing and transport burden or travel-time burden for representative households.	Household surveys, fare data, location/accessibility analysis	Household/population group	Requires explicit assumptions about income, modes and trip purposes.
Walkability and public realm	Continuity of pedestrian routes; safe crossings; street connectivity; public-space access; barrier-free access audit score.	Street audits, GIS, observation, community mapping	Street segment/neighbourhood	Composite scores should disclose weighting and accessibility standards.
Neighbourhood serviceability	Capacity and phasing fit of drainage, utilities, roads and social facilities with proposed housing growth.	Engineering/planning records, field audits, implementation reports	Phase/neighbourhood	Requires specialist capacity verification, not GIS proximity alone.
Resident experience	Resident satisfaction with access, safety, services, public realm and neighbourhood usability; complaints/defect patterns.	Post-occupancy surveys, interviews, service/complaint records	Household / demographic group	Subjective results should be disaggregated and triangulated with measured conditions.
Implementation cost and effort	Data acquisition/maintenance cost; analysis and training cost; time to update evidence; infrastructure/retrofit cost implications.	Project accounts, agency records, implementation logs	Project/institution	Used to judge incremental value, not only technical sophistication.
Model performance and uncertainty	Classification/prediction accuracy where applicable; sensitivity of suitability	Model logs, validation dataset,	Model/scenario	Metric must match method; high accuracy

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	rankings to weights/thresholds; validation error.	sensitivity analysis		does not establish normative legitimacy.
Governance compliance	Data provenance documented; privacy review completed; excluded groups/areas assessed; responsible reviewers named; appeal/challenge mechanism available.	Governance checklist, decision records, audit trail	Decision/project	Compliance should be substantive and auditable, not a tick-box substitute for participation.

Source. Authors' synthesis based on urban-growth and land-use evidence (Angel et al., 2011; Seto et al., 2012), accessibility and infrastructure research (Coutinho-Rodrigues et al., 2011; Davern et al., 2017; Iamtrakul et al., 2024; Parry et al., 2018), housing-location evidence (Ayoola et al., 2023; Borth et al., 2024), GeoAI and model-validation literature (Casali et al., 2022; Chaturvedi & de Vries, 2021), responsible-AI governance (ISO, 2023; OECD, 2024; UNESCO, 2021), Nigerian data-protection requirements (Nigeria Data Protection Act, 2023), and Nigerian urban evidence (Ajagbe et al., 2021; Olofin & Oluwadare, 2022; World Bank, 2025).

Note: These are candidate indicators for empirical pilot testing, not validated national standards. Each project should predefine units, baselines, thresholds, update intervals and required disaggregation before analysis.

Limitations and research agenda

This review is limited by its structured narrative rather than systematic or meta-analytic design, dependence on published evidence, heterogeneous geographic and methodological contexts, and absence of pooled effect estimates or a formal numerical risk-of-bias instrument. The search strategy did not constitute a fully reproducible database search, and publication or language bias cannot be excluded. Much of the GeoAI evidence originates outside Nigerian secondary cities, while direct empirical evidence connecting GeoAI-derived site analysis to completed architectural neighbourhood outcomes is limited. Intermediate screening-flow counts were not preserved in the available review record. The proposed framework has not been tested through local modelling, stakeholder workshops, design evaluation or implementation trials. It should therefore be interpreted as a conceptual, testable decision framework rather than a validated protocol. The Ado-Ekiti discussion is illustrative and deliberately avoids presenting unmeasured local conditions as empirical findings.

Future research should test the framework through comparative multi-site pilots using current spatial datasets, field surveys, professional and community validation, transparent suitability criteria, sensitivity analysis and architectural design testing. Baseline or comparison decision processes should be included where feasible to determine whether GeoAI-assisted workflows provide measurable incremental benefits in site selection, infrastructure sequencing, design quality, service access, environmental risk management, implementation cost and post-occupancy outcomes. Research should also evaluate model maintenance, data governance, institutional capacity and how performance varies across different categories of Nigerian secondary cities.

CONCLUSION

The reviewed evidence indicates that geospatial analysis can improve the visibility of urban-growth pressure, service gaps, environmental constraints and candidate housing locations. At the same time, GeoAI-specific methods may augment selected prediction, classification and pattern-recognition tasks. These outputs remain decision-support evidence rather than development decisions (Casali et al., 2022; Chaturvedi & de Vries, 2021; Mortaheb & Jankowski, 2023). Planning judgement, architectural translation, statutory review, specialist verification and public validation remain necessary where model outputs affect housing location and neighbourhood form (Othengrafen et al., 2025; Sanchez et al., 2025; UNESCO, 2021).

The article contributes a proposed integrated architecture-planning decision framework in which Urban and Regional Planning interprets growth, suitability, infrastructure, participation and development-control evidence. At the same time, Architecture translates preferred planning options into liveable, climate-responsive and service-aware neighbourhood alternatives. The framework explicitly separates conventional geospatial analysis from AI-specific functions and treats monitoring, post-occupancy learning and governance as integral parts of the decision cycle. It remains conceptual pending empirical validation.

For Ado-Ekiti and comparable secondary cities, empirical evaluation should determine whether the integrated workflow provides measurable incremental benefits over existing decision processes in housing-location selection, infrastructure sequencing, neighbourhood-design quality, service accessibility, environmental risk management, resident experience and post-occupancy learning. The central proposition is therefore not that GeoAI determines where or how cities should grow, but that selectively used GeoAI can strengthen a broader, transparent geospatial evidence system when interpreted through accountable planning, architectural design and community review.

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Supplementary Material

Supplementary Table S1: Reproducible search specification for the structured narrative review

Source	Search block	Reproducible search expression/approach	Window/ update	Purpose	Transparency note
Google Scholar	GeoAI / urban AI	("GeoAI" OR "artificial intelligence" OR "machine learning") AND ("urban planning" OR "land-use planning" OR "housing growth")	2010-2025; update 30 Jul 2026	Broad discovery of AI/ML-geospatial planning literature	Historical result counts were not preserved; query operationalises the reported concepts.
Google Scholar	Urban growth modelling	("urban growth modelling" OR "urban expansion" OR "urban sprawl") AND (GIS OR "remote sensing" OR "spatial simulation" OR "cellular automata")	2010-2025; update 30 Jul 2026	Growth detection, modelling and scenario evidence	Conventional spatial simulation treated separately from AI/ML.
Google Scholar	Housing-location suitability	("housing location" OR "residential location" OR "land suitability") AND (GIS OR accessibility OR infrastructure OR affordability)	2010-2025; update 30 Jul 2026	Residential location, site suitability and accessibility evidence	Site-selection criteria considered where planning relevance was explicit.
Google Scholar	Planning support and infrastructure	("planning support system" OR "spatial decision support") AND (infrastructure OR accessibility OR housing OR urban)	2010-2025; update 30 Jul 2026	Planning-support, infrastructure sequencing and MCDA evidence	Planning-support systems not automatically classified as AI.
Google Scholar	Nigeria / Africa	(Nigeria OR Nigerian OR Africa) AND (urbanisation OR "land use" OR "urban expansion" OR "secondary cities" OR housing) AND (GIS OR "remote sensing" OR planning)	2010-2025; update 30 Jul 2026	Contextual Nigerian/African urbanisation and land-change evidence	Contextual evidence weighted for transferability, not treated as proof of GeoAI performance.
Scopus-indexed journals/ publisher platforms	Targeted verification	Topic combinations above, targeted to relevant titles and publisher search interfaces	Updated 30 Jul 2026	Verification and retrieval of peer-reviewed analytical sources	Targeted journal/platform searching, not a fully reproducible Scopus database export.
Institutional /statutory sources	Governance and policy	Targeted title/institution searches for Architects Act; Town Planners Act; Nigeria Data Protection Act;	Current authoritative editions used	Policy, statutory, responsible-AI and planning context	Supplementary normative/contextual evidence; excluded from

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		National AI Strategy; ISO/IEC 23894; OECD AI Principles; UNESCO AI Ethics; UN-Habitat planning guidance			the 46-article analytical count.

Note: The table reconstructs a reproducible operational search specification from the concepts reported in the manuscript. Because historical database-export files and intermediate record counts were not available in the review record, those values are not invented. The analytical corpus remains 46 peer-reviewed articles assigned to one dominant counting theme, with methodological, policy, statutory and governance sources treated separately.