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Impediments to Machine Learning Adoption for Land Use Change Prediction: Perceptions of Registered Land Use Professionals in Akure, Nigeria

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Abstract

Recent advances in machine learning (ML) have created new opportunities for improving the prediction of urban land use change. Despite these prospects, the adoption of ML techniques among land use professionals in Nigerian cities remains limited due to several structural, institutional, technical, and resource-related challenges. This study examined the barriers to the adoption of machine learning for land use change prediction in Akure, Ondo State, Nigeria, from the perspective of registered land use professionals. A census survey was conducted among 86 professionals comprising Estate Surveyors and Valuers, Town Planning officials, Land Surveyors, and GIS/Remote Sensing experts, out of which 64 valid responses were retrieved, representing a 74% response rate. Data obtained from the survey were analyzed using descriptive statistics, including frequency distribution, percentages, Relative Importance Index (RII), and Weighted Mean Score (WMS). Twenty-two identified barriers were grouped into four categories: data-related barriers, model-related barriers, policy and institutional barriers, and computational/other barriers. The findings from the study revealed a Grand RII of 0.8338, indicating that respondents generally perceived the identified barriers as highly significant. Poor internet connectivity (RII = 0.9250) and funding/resource constraints (RII = 0.9250) ranked as the most severe impediments to ML adoption, followed by inadequate computing infrastructure (RII = 0.9031) and continued dependence on traditional methods (RII = 0.8938). The study concludes that infrastructural and resource deficiencies, rather than professional

resistance are the major factors limiting the adoption of ML tools in the study area. The research therefore recommended improved digital infrastructure, increased institutional support, enhanced professional training, and better access to geospatial data to facilitate the integration of ML into land use planning practice in Nigeria.

Keywords: Machine learning; urban land use change; land use professionals; adoption barriers; land use change prediction.

Introduction

Land use change has become one of the major drivers of urban transformation in many developing countries, where rapid urbanization continues to reshape the physical and socio-economic structure of cities. Changes in land use patterns have significant implications for urban planning, environmental sustainability, infrastructure provision, housing development, and property markets (Daramola & Eresanya, 2021; Frontiers in Sustainable Cities, 2024). As cities expand and peri-urban areas experience increasing development pressure, the need for accurate and timely land use monitoring and prediction has become increasingly important for effective planning and policy formulation.

In recent years, machine learning (ML) techniques have emerged as important tools for land use and land cover (LULC) classification and change prediction. Algorithms such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forest (RF) have demonstrated high levels of accuracy in analyzing complex spatial datasets and predicting land use dynamics across different urban environments (Koutra & Ioakimidis, 2023). Compared with conventional classification approaches, ML techniques are more effective in handling large volumes of geospatial data and identifying non-linear relationships within spatial datasets. Consequently, they are increasingly being applied in urban growth modelling, environmental monitoring, and spatial decision-making processes (Tamiminia et al., 2022).

Despite these advantages, the adoption of ML-based approaches among land use professionals in many Nigerian cities remains relatively low. Professionals involved in estate surveying, urban and regional planning, land surveying and geospatial analysis still rely heavily on traditional analytical and cartographic methods for land use studies (Aiguobarueghian et al., 2025). Although these conventional methods remain useful, they are often limited in their ability to capture the complexity and rapid pace of contemporary urban land use transformation (Vibbi, 2024).

Akure, the capital city of Ondo State, provides a suitable context for examining these challenges. The city has experienced rapid urban expansion in recent years, particularly through the conversion of vegetation and peri-urban land into residential and commercial uses (Adewoyin et al., 2025). This increasing rate of land transformation has created a growing need for efficient land use monitoring and

predictive tools that can support sustainable urban planning and development management. However, the technological and institutional conditions required for the effective deployment of ML applications in land use practice remain insufficient within the study area.

Although previous studies have examined machine learning applications in urban planning and geospatial analysis, much of the existing literature has focused on developed countries or broader policy discussions (ScienceDirect, 2025; OECD, 2025). Empirical studies investigating the specific barriers to ML adoption among land use professionals in Nigerian cities are still limited. More importantly, there is little evidence from secondary cities such as Akure, where infrastructural and institutional limitations are often more pronounced. This study therefore seeks to fill this gap by examining the perceptions of registered land use professionals regarding the barriers associated with machine learning adoption for land use change prediction in Akure, Nigeria.

The specific objective of the study is to assess the perceived impediments to the adoption of machine learning techniques for land use change prediction among registered land use professionals in the study area. The study contributes to the growing discourse on digital transformation in land administration and urban planning practice in developing countries. It also provides empirical evidence that may assist policymakers, professional bodies, and academic institutions in developing strategies to improve the adoption and application of ML technologies in land use management and spatial planning activities.

Machine Learning in Land Use Change Prediction

Machine learning has increasingly become an important analytical approach in land use and land cover (LULC) studies due to its ability to process large and complex geospatial datasets with high levels of accuracy. Conventional land use classification techniques, such as maximum likelihood classification and manual image interpretation, are often limited in their capacity to effectively analyze high-dimensional spatial data and rapidly changing urban environments (Jemeljivanova et al., 2024). In contrast, machine learning algorithms are capable of identifying patterns within datasets and generating predictive models without the need for explicitly programmed classification rules.

Among the commonly applied ML algorithms in land use studies are Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forest (RF). ANN models simulate the structure of the human brain and are particularly effective in modelling complex and non-linear relationships between spatial variables. SVM techniques are widely used for classification tasks because they are capable of separating land use classes within high-dimensional feature spaces with high precision. Random Forest algorithms, on the other hand, utilize multiple decision trees to improve classification accuracy and minimize the risk of overfitting (Tamiminia et al., 2022; Georganos et al., 2021). These algorithms have been applied extensively in urban growth modelling, environmental monitoring, and land use prediction studies across different regions of the world.

Several empirical studies have demonstrated the effectiveness of ML techniques in land use analysis. Aiguobarueghian et al. (2025) employed Normalized Difference Vegetation Index (NDVI)-based machine learning classification to assess land cover change and urban expansion in Benin City, Nigeria, and reported significant growth in built-up areas between 2014 and 2024. Similarly, Adewoyin et al. (2025) examined peri-urban land use conversion in Ibadan using satellite imagery and GIS techniques and found that ML-based classification produced more detailed and reliable outputs than traditional mapping approaches. Addae and Dragicevic (2024) further demonstrated that the integration of deep learning into geospatial simulation models significantly improved the accuracy of global land use and land cover projections.

At the broader urban planning level, Koutra and Ioakimidis (2023) highlighted the growing relevance of machine learning applications in addressing urban planning challenges, including land use management, infrastructure planning, and environmental sustainability. It was noted in the study that while ML technologies possess significant transformative potential, practical implementation remains difficult in many developing countries due to infrastructural and institutional limitations. This suggests that the successful integration of ML into land use practice depends not only on the availability of analytical tools but also on the capacity of institutions and professionals to effectively utilize them.

Technology Adoption Barriers in Urban Planning Practice

The adoption of advanced technologies in urban planning and land management practice has attracted growing scholarly attention in recent years. Despite the increasing availability of planning support systems and digital analytical tools, their practical application among professionals remains relatively limited in many contexts. This situation has been described in the literature as the "planning support system implementation gap," which refers to the disconnect between technological development and actual professional usage (ScienceDirect, 2025).

Several studies have identified different barriers affecting the adoption of digital and AI-based technologies in urban planning practice. Ye et al. (2023) identified concerns relating to model accuracy, lack of technical expertise, insufficient training opportunities, and weak institutional support as key factors limiting the adoption of AI-driven planning tools. Andrews et al. (2022) also observed that many planning professionals remain uncertain about the reliability and accountability of AI-generated outputs, especially where planning decisions may have significant legal, environmental, or economic implications.

In developing countries, however, infrastructural and resource-related constraints appear to be more dominant. Vibbi (2024) noted that poor data quality, inadequate digital infrastructure, and limited access to technological resources continue to hinder the deployment of artificial intelligence applications across Sub-Saharan Africa. Similarly, GSMA (2024) identified unstable electricity supply and weak broadband connectivity as major structural barriers to digital transformation in Nigerian urban centres. These limitations significantly reduce the

ability of professionals and institutions to effectively utilize cloud-based geospatial platforms and machine learning tools.

Data-related challenges also remain a major concern in ML adoption. Abdulmuttalib et al. (2024) argued that inconsistencies in spatial datasets, low-resolution imagery, and incomplete geospatial information can negatively affect the performance and reliability of machine learning models. This challenge is particularly severe in many Nigerian cities where regular land use mapping and geospatial data updates are often inadequate. Discover Cities (2025) further observed that the high cost of acquiring geospatial datasets, specialized hardware, and technical expertise contributes to the widening technological gap between developed and developing countries.

Although previous studies have examined artificial intelligence adoption and GIS applications in planning practice, empirical evidence focusing specifically on machine learning adoption among registered land use professionals in Nigerian cities remains limited. Existing studies have largely concentrated on policy-level discussions or broader technological adoption issues without examining the practical experiences of professionals directly involved in land administration, surveying, urban planning, and geospatial analysis (Morenikeji et al., 2023). Consequently, there is still insufficient understanding of the specific barriers affecting the operational use of machine learning tools for land use change prediction in secondary Nigerian cities such as Akure.

This study therefore contributes to the existing body of knowledge by providing empirical evidence on the perceptions of registered land use professionals regarding the impediments to machine learning adoption for land use change prediction in Akure, Nigeria.

Study Area

The study was conducted in Akure, the capital and largest city of Ondo State, southwest Nigeria. Akure is located approximately at latitude 7°15'N and longitude 5°10'E and lies within Nigeria's tropical rainforest zone at an elevation of approximately 370 metres above sea level. The city had a population of 484,798 at the 2006 National Population Census, comprising 353,211 in Akure South LGA and 131,587 in Akure North LGA with current estimates placing the metropolitan population at approximately 774,000 (Wikipedia, 2024; National Population Commission, 2006).

Akure became the capital of Ondo State following its creation in 1976 and has since grown into the principal administrative, educational, and commercial centre of the state. The study area encompasses two Local Government Areas: Akure South, which covers an area of approximately 331 km² with its headquarters at Akure city, and Akure North, which covers approximately 660 km² with its headquarters at Iju/Itaogbolu. Akure South is bounded on the north-east by Akure North LGsA, on the north-west by Ifedore LGA, and on the south by Idanre LGA. The two LGAs constitute the administrative and functional extent of the Akure urban agglomeration and its immediate peri-urban fringe, the zone in which land use change pressure is most intense. The annual temperature typically ranges from 18 to 31°C, with a major rainy season from April to October. The study area hosts key institutions including the

Federal University of Technology Akure (FUTA), which provides the institutional base for the GIS and Remote Sensing professional group surveyed in this study

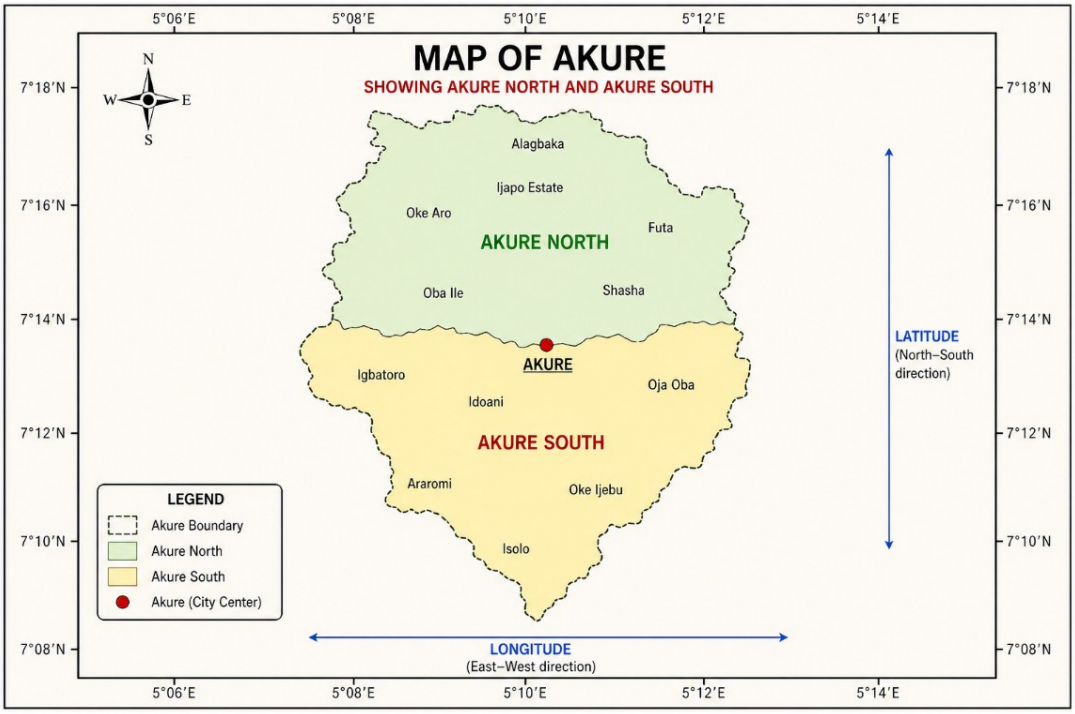


Figure 1

Research Design

This study adopted a survey research design to examine the perceptions of registered land use professionals regarding the barriers associated with the adoption of machine learning for land use change prediction in Akure, Nigeria. The survey approach was considered appropriate because the study focused on obtaining opinions and professional assessments from respondents concerning the challenges affecting the application of ML techniques in land use practice.

Primary data were collected through the administration of structured questionnaires to relevant professionals within the study area. The questionnaire was designed to capture both the demographic characteristics of respondents and their perceptions of identified barriers to machine learning adoption. The use of a structured survey instrument ensured uniformity in data collection and enabled the responses to be analyzed quantitatively.

The study relied mainly on quantitative methods of analysis. Data obtained from the field survey were analyzed using descriptive statistical tools, including frequency distribution, percentages, Relative Importance Index (RII), and Weighted Mean Score (WMS). These analytical techniques were adopted to determine the severity and relative significance of the identified barriers based on respondents' perceptions. The approach also enabled the ranking of the barriers according to their level of importance among the surveyed professionals.

Survey Instrument and Target Population

The primary data for the perception survey were collected through a structured questionnaire administered to registered land use professionals in Akure. The questionnaire consisted of two parts: Part A captured the demographic and professional profile of respondents; Part B presented 22 barrier items on a five-point Likert scale ranging from Strongly Disagree (1) to Strongly Agree (5). The 22 items were grouped into four thematic categories: data-related barriers, model-related barriers, policy and institutional barriers, computational/other barriers. The questionnaire items were derived from an extensive review of the ML adoption and GeoAI literature and were pre-tested with five professionals before administration to ensure clarity and face validity.

The target population comprised all registered and practicing land use professionals in Akure. This population was identified through official directories and institutional registers. A census approach was adopted meaning every member of the sampling frame was included in the study eliminating sampling error and maximizing representativeness within the defined population. Table 1 presents the target population, sampling frame, sampling size, and sources of information for each professional group.

Table 1: Target Population, Sampling Frame, and Sampling Size

S/N	Target Population	Sample Frame	Sampling Size	Source of Information
1	Estate Surveyors and Valuers in Estate Surveying and Valuation Firms	30	30 (Census)	2024 Directory of NIESV, Ondo State Chapter
2	Registered Town Planning Officials	33	33 (Census)	Ministry of Lands and Physical Planning, Akure
3	Land Surveyors	13	13 (Census)	Ministry of Lands and Physical Planning, Akure
4	GIS and Remote Sensing Experts	10	10 (Census)	Department of GIS and Remote Sensing, FUTA, Akure
Total		**86**	**86**	

Source: Author's field survey, 2026

Table 2 summarizes the administration and retrieval of questionnaires across the four professional groups.

Table 2: Questionnaire Administration and Response Rate

Professional Group	Questionnaire Administered	Questionnaire Retrieved	Response Rate (%)
Estate Surveyors and Valuers	30	26	87
Registered Town Planning Officials	33	21	64
Land Surveyors	13	11	85

Professional Group	Questionnaire Administered	Questionnaire Retrieved	Response Rate (%)
GIS and Remote Sensing Experts	10	6	60
Total	**86**	**64**	**74**

Source: Author's field survey, 2026

A total of 86 questionnaires were administered and 64 were retrieved and found valid for analysis, representing an overall response rate of 74%. This response rate is considered adequate for a census-based professional survey, consistent with acceptable thresholds of 60% or above recommended in social science research (Mugenda & Mugenda, 2003).

Data Analysis

The perception data were analyzed using two complementary quantitative methods: the Weighted Mean Score (WMS) and the Relative Importance Index (RII). The WMS was computed as the sum of the products of each scale value and its frequency, divided by the total number of respondents. A Grand Mean of 4.17 was adopted as the significance threshold, above which a barrier was classified as highly significant. The RII was computed using the formula: $RII = \Sigma W / (A \times N)$

Where ΣW is the sum of weighted scores, A is the highest scale weight (A = 5), and N is the total number of respondents (N = 64). The RII produces a normalized index between 0 and 1, with higher values indicating greater perceived severity. A Grand RII of 0.8338, computed as the mean RII across all 22 items, served as the complementary significance threshold. Barriers were ranked by RII in descending order; tied values were assigned shared ranks. The convergence between RII and WMS rankings was used to validate the internal consistency of findings across both methods.

Barriers to Machine Learning Adoption: RII and WMS Analysis

Table 3 presents the results of the RII and WMS analysis of the 22 barrier items across the four thematic categories. The Grand RII of 0.8338 indicating that professionals reached 83.38% of maximum possible consensus on barriers collectively confirms that ML adoption impediments are pervasive and deeply felt across all professional groups in Akure. The perfect concordance between RII and WMS rankings across all 22 items validates the robustness of the findings.

Table 3: Barriers to Machine Learning Adoption — RII and WMS Results (N = 64)

S/N	Category	Barrier	SD(1)	D(2)	FA(3)	A(4)	SA(5)	ΣW	RII	RII Rank	WMS	WMS Rank
1	Data-Related	Access to high-quality data for land-use modeling is limited.	1	2	4	24	33	278	0.8688	6th	4.34	6th
2	Data-Related	The available data for analysis are often inconsistent or incomplete.	0	3	6	30	25	269	0.8406	10th	4.20	10th
3	Data-Related	Data used for land-use studies often have low spatial or temporal resolution.	1	2	6	39	16	259	0.8094	13th	4.05	13th

S/N	Category	Barrier	SD(1)	D(2)	FA(3)	A(4)	SA(5)	ΣW	RII	RII Rank	WMS	WMS Rank
4	Data-Related	It is difficult to integrate data from multiple sources for analysis.	0	4	18	29	13	243	0.7594	22nd	3.80	22nd
5	Data-Related	Concerns about data privacy and security limit data sharing and collaboration.	0	2	9	34	19	262	0.8187	12th	4.09	12th
6	Model-Related	Selecting the most appropriate ML algorithm is often challenging.	0	2	14	29	19	257	0.8031	15th	4.02	15th
7	Model-Related	Model outputs are sometimes difficult to interpret or explain.	1	5	12	33	13	244	0.7625	21st	3.81	21st
8	Model-Related	Models developed for one region do not generalize well to other regions.	0	3	10	35	16	256	0.8000	16th	4.00	16th
9	Model-Related	Model performance is often affected by overfitting or underfitting problems.	0	3	14	33	14	250	0.7812	18th	3.91	18th
10	Model-Related	There is uncertainty about the accuracy of ML models in land-use prediction.	0	4	13	34	13	248	0.7750	20th	3.87	20th
11	Policy & Institutional	There is inadequate government/organizational support for applying ML.	0	1	8	33	22	268	0.8375	11th	4.19	11th
12	Policy & Institutional	Regulatory and privacy restrictions limit access to necessary data.	0	0	11	39	14	259	0.8094	13th	4.05	13th
13	Policy & Institutional	Absence of standardized land-use classification methods hampers analysis.	1	1	12	38	12	251	0.7844	17th	3.92	17th
14	Policy & Institutional	Policymakers and stakeholders resist adoption of new technologies.	0	4	11	37	12	249	0.7781	19th	3.89	19th
15	Computational	The computational cost of running advanced models is very high.	0	1	7	29	27	274	0.8562	9th	4.28	9th
16	Computational	Inadequate access to advanced computing resources for model development.	0	1	9	22	32	277	0.8656	7th	4.33	7th
17	Computational	Limited expertise in ML and data science among professionals.	1	1	9	18	35	277	0.8656	7th	4.33	7th
18	Computational	Deploying and maintaining ML models is difficult due to technical constraints.	0	1	7	21	35	282	0.8812	5th	4.41	5th
19	Other	Professionals still rely heavily on traditional methods instead of ML.	0	3	4	17	40	286	0.8938	4th	4.47	4th
20	Other	Poor internet connectivity affects access to cloud-based data platforms.	0	0	5	14	45	296	0.9250	1st	4.63	1st
21	Other	Computing infrastructure for large-scale data analysis is insufficient.	0	0	5	21	38	289	0.9031	3rd	4.52	3rd
22	Other	Funding and resource constraints limit the effective application of ML tools.	0	1	5	11	47	296	0.9250	1st	4.63	1st
		Grand RII / Grand WMS							**0.8338**		**4.17**	

Source: Author's field survey, 2026

Discussion of Key Findings

The findings of this study indicate that poor internet connectivity and funding/resource constraints are the most critical barriers affecting the adoption of machine learning for land use change prediction in Akure. Both variables recorded the highest Relative Importance Index (RII = 0.9250) and Weighted Mean Score (WMS = 4.63), reflecting a strong level of agreement among respondents. This suggests that the absence of reliable digital infrastructure

and adequate financial resources significantly limits the ability of professionals to access, implement, and sustain ML-based applications in land use practice. The finding supports the position of Vibbi (2024) and GSMA (2024), who identified weak digital infrastructure, unstable connectivity, and limited technological investment as major constraints to AI deployment in many Sub-Saharan African cities.

The result further shows that inadequate computing infrastructure and continued reliance on traditional methods are among the most significant impediments to ML adoption in the study area. The high ranking of these barriers suggests that many professionals still depend on conventional land use analysis techniques due to the limited availability of modern computational facilities and specialized software tools. This dependence on traditional methods may not necessarily indicate resistance to innovation, but rather an adaptation to existing institutional and infrastructural realities. The finding aligns with Rogers' (2003) diffusion of innovations theory, which emphasizes that the adoption of new technologies is strongly influenced by accessibility, compatibility, and observable advantages within a given environment.

The study also revealed that limited access to high-quality spatial data remains a major data-related challenge. Respondents indicated that geospatial datasets required for ML applications are often incomplete, inconsistent, or difficult to obtain. This finding is consistent with Abdulmuttalib et al. (2024), who observed that poor-quality spatial data can significantly reduce the effectiveness and reliability of machine learning models. In many Nigerian cities, regular land use mapping and geospatial database updates are still inadequate, thereby affecting the quality of input data available for predictive modelling and spatial analysis.

Another important finding is the limited level of expertise in machine learning and data science among land use professionals. Respondents acknowledged that the shortage of technical knowledge and specialized training constrains the practical application of ML tools in professional practice. This indicates the existence of a significant human capacity gap within the land use sector. The finding supports previous studies which argued that the successful integration of AI and ML technologies depends heavily on the availability of trained personnel and continuous professional development opportunities (Ye et al., 2023; Tamiminia et al., 2022).

Among the policy and institutional barriers examined, inadequate government and organizational support ranked highest. This suggests that professional bodies and relevant government agencies have not yet provided sufficient institutional frameworks, funding support, or policy direction to encourage the adoption of ML technologies in land use management practice. Regulatory restrictions relating to data access and the absence of standardized land use classification systems further compound these challenges. However, barriers relating to model accuracy, overfitting, and algorithm selection recorded relatively lower rankings compared with infrastructural and resource-related factors. This implies that professionals in the study area are more constrained by access and operational issues than by the technical limitations of the models themselves.

Collectively, the findings demonstrated that the barriers to machine learning adoption in Akure are largely structural, institutional, and resource-related. The study therefore suggested that improving digital infrastructure, expanding access to geospatial data, strengthening institutional support, and enhancing professional capacity development are essential steps toward promoting the effective integration of machine learning into land use planning and urban management practice in Nigeria.

Conclusion and Recommendations

This study examined the impediments to the adoption of machine learning for land use change prediction among registered land use professionals in Akure, Nigeria. The findings revealed that the application of ML techniques in land use practice is still constrained by several interrelated challenges, particularly poor internet connectivity, inadequate funding, insufficient computing infrastructure, limited access to quality spatial data and inadequate technical expertise among professionals. The study established that these barriers are primarily structural and institutional rather than attitudinal as most respondents showed recognition of the potential usefulness of machine learning tools in land use analysis and prediction.

The study further demonstrated that infrastructural deficiencies remain the most significant obstacle to the effective deployment of ML technologies within the study area. Although machine learning offers considerable advantages for urban land use monitoring, classification, and prediction, the absence of the required digital and technical support systems continues to limit its practical application among professionals involved in land administration, urban planning, surveying, and geospatial analysis in Akure. The findings therefore highlight the existing gap between technological advancement and operational capacity within the Nigerian land use sector.

Based on the findings, the study recommended that government at federal, state, and local levels should prioritize investment in digital infrastructure, particularly broadband internet access and stable electricity supply, to support the integration of advanced technologies into land use practice. Improved infrastructure will enhance access to cloud-based geospatial platforms, digital datasets and machine learning applications.

Professional bodies such as the Nigerian Institution of Estate Surveyors and Valuers, Nigerian Institute of Town Planners and Surveyors Council of Nigeria should strengthen capacity-building programmes by incorporating machine learning, data science, GIS, and GeoAI training into their continuing professional development activities. Such initiatives will improve the technical competence of professionals and encourage the practical adoption of ML tools in land use management.

The study also recommended that relevant government agencies and academic institutions should promote the development of accessible geospatial data repositories containing current and standardized land use datasets. Increased access to reliable spatial data will reduce one of the major barriers identified by respondents and improve the effectiveness of ML-based analysis and prediction.

Furthermore, higher institutions offering land-related programmes should expand the integration of machine learning and geospatial analytics into their academic curricula. This will help prepare future professionals with the technical knowledge required for emerging digital planning and land management systems. Collaborative partnerships between universities, government agencies, and private technology organizations should also be encouraged to facilitate research, training, and technology transfer.

Finally, future studies should extend similar investigations to other Nigerian cities in order to determine whether the barriers identified in Akure reflect broader national trends. Comparative studies across different urban centres may provide deeper insight into regional variations in technological readiness and institutional capacity for machine learning adoption in land use planning practice.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this research.

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