

The Application of Parametric and Non-Parametric Models in Analysing Urban Expansion in the South-South Nigeria

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ABSTRACT

This paper applies parametric and non-parametric models in analysing urban growth patterns in the South-South region of Nigeria. A mixed-methods framework integrating geospatial analysis, statistical techniques, and machine learning was adopted. Landsat imagery (1993, 2003, 2013, and 2023) was processed through supervised Land Use/Land Cover classification, and an Urban Expansion Index (UEI) was computed to evaluate growth efficiency. Physical factors such as elevation and slope, infrastructural variables including proximity to highways, central business districts, and ports, and socio-economic attributes, such as access to markets and population density, were derived from spatial analysis and complemented with questionnaire data. Parametric models (linear and logistic regression) were compared with non-parametric approaches (Multi-Layer Perceptron Neural Networks, Random Forest, and Geographically Weighted Regression). Findings reveal significant urban sprawl across all cities studied, with Benin City's urban footprint rising from 13.7% in 1993 to 29.2% in 2023, and Port Harcourt's from 10.5% to 36.8%. Key drivers included population growth, industrialisation, and proximity to infrastructural hubs, while elevation constrained development. Non-parametric models outperformed parametric ones, highlighting complex non-linear dynamics. The study details the strengths and limitations of each modeling approach and their effectiveness in capturing the complexities of urban expansion. The implications of these findings for urban planning and future research are discussed.

Keywords: *Urban expansion, parametric model, non-parametric model, Random Forest, urban growth, urbanisation*

INTRODUCTION

Urban expansion is a global trend that is significantly altering the world's landscape, with profound consequences for environmental sustainability, economic systems, and social well-being. This phenomenon is evident in diverse contexts, and the South-South region of Nigeria is no exception. Here, rapid urban growth is fueled by factors such as increasing populations, economic activity, particularly the oil industry, and the



development of new industries (Bayode & Siegmund, 2023). To ensure sustainable growth and effective future planning, a thorough understanding and accurate prediction of urban expansion patterns are essential. Urban expansion in the South-South region of Nigeria presents a complex phenomenon driven by various socio-economic and environmental factors.

The South-South region of Nigeria, which comprises Akwa Ibom, Bayelsa, Cross River, Delta, Edo, and Rivers States, provides a particularly important case study of these issues. The region is strategically important to Nigeria because of its abundant natural resources, particularly crude oil and natural gas, which have spurred economic growth and industrialisation since the oil boom of the 1970s. Cities such as Port Harcourt, Benin City, Uyo, Asaba, Yenagoa, and Calabar have expanded rapidly, fueled by industrialisation, migration, and infrastructural development projects. However, this expansion has been largely unplanned and unregulated, leading to uncontrolled urban sprawl, loss of agricultural land, encroachment into wetlands and forested areas, and increased exposure to environmental hazards. In Port Harcourt, for instance, urban growth has increasingly taken place in low-lying flood-prone zones, aggravating drainage challenges and heightening flood risks. Similarly, Benin City and Asaba have witnessed the conversion of peri-urban farmlands into settlements, reducing food production capacity and threatening rural livelihoods.

To achieve this understanding, researchers employ a variety of analytical tools, including mathematical models. These models can be broadly categorised as parametric and non-parametric. Parametric models, such as linear regression, operate under the assumption of a specific, pre-defined functional relationship between variables. Conversely, non-parametric models, including techniques like neural networks and Random Forest, offer greater flexibility by relaxing these assumptions, enabling them to capture more complex and less predictable patterns. In this paper, we aim to compare the performance of parametric and non-parametric models in analysing urban expansion within the South-South region of Nigeria. Specifically, we evaluate the advantages and limitations of each modeling approach and assess their effectiveness in explaining the complexities of urban growth in this context.

Study Area

The South-South region of Nigeria is located in the southern part of the country and comprises the following States: Akwa Ibom, Bayelsa, Cross River, Delta, Edo, and Rivers. The region is characterised by a coastal landscape, extensive river networks (including the Niger Delta), and a tropical climate. Key cities in the region include Port Harcourt, Benin City, Calabar, and Uyo. The South-South region is a major economic hub in Nigeria, primarily due to its rich deposits of crude oil and natural gas. The oil industry has attracted significant investment and migration to the area, driving economic activities such as petroleum exploration, refining, and related services. Other important

economic sectors include agriculture, fishing, and trade. The region has a diverse population, with various ethnic groups, including the Ijaw, Edo, Efik, and others.



Figure 1: Map of Nigeria highlighting states in the South-South Region

Data Sources

The study utilised a combination of satellite imagery and other data sources to analyse urban expansion in the South-South region of Nigeria. The following table provides a summary of the data types and their sources:

Data Type	Description	Source(s)
Satellite Imagery	Landsat 5 TM, Landsat 7 ETM+, and Landsat 8 OLI/TIRS images	United States Geological Survey (USGS) Earth Explorer
Socio-economic Data	Population statistics, economic indicators, and infrastructural data	National Bureau of Statistics (NBS), relevant state government agencies
GIS Data	Digital elevation models, road networks, and administrative boundaries	Open Street Map, Shuttle Radar Topography Mission (SRTM)

METHOD

Urban Expansion Index

In order to derive the urban area, land use land cover classification for year 1993 and 2023 was done using the Maximum Likelihood Approach. This enabled the derivation of the extent of urban expansion for the south-south region. Change detection was used to identify and quantify the changes in urban land area over the study period. This involved comparing the land cover maps between 1993 and 2023 to determine the extent and location of urban expansion. The Urban Expansion Index (UEI) is calculated to quantify the rate and pattern of urban expansion (Manesha et al., 2021). The UEI is calculated as:

$$UEI = \frac{Urban\ Area_{t2} - Urban\ Area_{t1}}{Urban\ Area_{t1} \times (t_2 - t_1)}$$

Where:

- Urban Area t_1 is the urban area at the initial time (t_1).
- Urban Area t_2 is the urban area at the final time (t_2).
- $t_2 - t_1$ is the time interval.

Parametric Modeling Approach

Parametric models are statistical models that assume a specific functional form for the relationship between the dependent and independent variables. In the context of urban expansion, common parametric models used include linear regression.

• Linear Regression

Linear regression is a fundamental parametric statistical technique used to model the relationship between a dependent variable and one or more independent variables. Linear regression is used to model the relationship between a continuous dependent variable (the extent of urban expansion) and one or more independent variables (e.g., distance to highways, population density) (Nayak & Abdullah, 2020). The assumptions of linear regression include linearity, independence, homoscedasticity (constant variance of errors), and normality of errors. The basic formula for linear regression is:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon$$

Where:

- Y is the dependent variable (in this case, urban expansion).
- X_1, X_2, \dots, X_n are the independent variables (e.g., population density, distance from roads).
- β_0 is the y-intercept.
- $\beta_1, \beta_2, \dots, \beta_n$ are the coefficients that represent the change in Y for a unit change in X .
- ε is the error term.



Model validation involves assessing the performance of the parametric models using various metrics. For linear regression, common evaluation metrics include the coefficient of determination (R^2), mean squared error (MSE), and residual analysis. Linear regression is used to quantify the relationship between urban expansion and various socio-economic and spatial factors. The dependent variable is the change in urban land area over the study period, while the independent variables include population density, distance from major roads, distance from city centers, and other relevant factors.

The model was implemented using machine learning and statistical software. The data is split into training and testing sets to assess the model's performance. The model's performance is evaluated using metrics such as R-squared, Root Mean Squared Error (RMSE), and p-values to assess the significance of the independent variables.

Non-Parametric Modeling Approach

Non-parametric models do not assume a specific functional form for the relationship between the dependent and independent variables. Instead, they rely on the data to determine the structure of the model.

Random Forest

Random Forest is a non-parametric ensemble learning method that constructs a multitude of decision trees at training time (Ocheli et al., 2021). For regression tasks, the Random Forest outputs the mean prediction of the individual trees. Key aspects of Random Forest:

- *Bootstrap Aggregating (Bagging)*: Random Forest creates multiple subsets of the training data using bootstrap sampling (random sampling with replacement).
- *Random Subspace*: At each node in a decision tree, only a random subset of the features is considered for splitting. This decorrelates the trees and improves the model's generalisation ability.
- *Decision Tree Induction*: Each tree is grown to its maximum size without pruning.

Random Forest is employed to model the complex, non-linear relationships between urban expansion and its driving factors. The dependent variable is the change in urban land area, and the independent variables are the same as those used in the linear regression model. The Random Forest model is implemented using machine learning libraries. The model's hyperparameters, such as the number of trees and the number of features to consider at each split, are tuned using cross-validation. The model's performance is evaluated using metrics such as R-squared and RMSE.

Factors Influencing Urban Expansion in South-South Cities

This explained the variables that were considered in driving urban expansion, especially in the South-South cities. These factors are crucial in modeling urban expansion as they provide insights into the spatial dynamics of urban growth and the underlying drivers influencing the development of urban areas.

A. Distance to Highways

Highways are major transportation routes that facilitate the movement of people and goods. The proximity to highways can significantly influence urban growth as they provide easy access to other cities and regions, promoting economic activities and attracting businesses. Areas closer to highways often experience higher rates of development due to the convenience of transportation and the potential for increased commercial and residential activities (Girma *et al.*, 2022).

B. Distance to Rivers

Rivers have historically been crucial for the development of cities due to their role in providing water resources, transportation routes, and fertile land for agriculture. Proximity to rivers can influence urban growth by offering opportunities for trade, recreation, and tourism. However, it can also pose challenges such as flood risks, which need to be managed through proper urban planning and infrastructure development (Salam *et al.*, 2023).

C. Distance to the Central Business District (CBD)

The Central Business District (CBD) is the commercial and business hub of a city, characterised by high-density development, office buildings, and retail establishments. The distance to the CBD is a critical factor in urban growth as areas closer to the CBD tend to have higher land values and greater access to employment opportunities, services, and amenities. This proximity often drives residential and commercial development, leading to higher population densities and increased urbanisation (Otuoze *et al.*, 2021).

D. Distance to Markets

Markets are essential for the economic activities of a city, providing spaces for trade, commerce, and the exchange of goods and services. The proximity to markets can influence urban growth by attracting businesses and residents who seek convenient access to these economic hubs. Areas near markets often experience higher levels of development due to the economic opportunities they offer and the increased foot traffic they generate (Saleem, 2013).

E. Distance to Ports

Ports are critical infrastructure for cities with access to waterways, facilitating the import and export of goods and contributing to the economic growth of the region. The proximity to ports can drive urban growth by attracting industries related to shipping, logistics, and trade. Areas near ports often develop into industrial and commercial zones, supporting the economic activities associated with maritime trade (Salam *et al.*, 2023).

F. Distance to Major Roads

Major roads are vital for the connectivity and accessibility of urban areas, linking different parts of the city and providing routes for transportation and commuting. The distance to major roads can influence urban growth by enhancing the accessibility of an area, making it more attractive for residential, commercial, and industrial development. Areas with good road connectivity tend to experience higher rates of urbanisation due to the ease of movement and the potential for economic activities (Girma *et al.*, 2022).

G. Slope

Slope refers to the steepness or incline of the land surface. It is an important factor in urban growth as it affects the suitability of land for construction and development. Areas with gentle slopes are generally more favourable for urban development as they are easier to build on and less prone to erosion and landslides. Steeper slopes, on the other hand, can pose challenges for construction and may require additional engineering measures to ensure stability and safety. The slope also influences drainage patterns and the risk of flooding, which are important considerations in urban planning (Salam *et al.*, 2023).

H. Elevation

Elevation refers to the height of the land above sea level. It can influence urban growth by affecting the climate, accessibility, and risk of natural hazards. Areas at higher elevations may have cooler temperatures and different vegetation types, which can impact the suitability of the land for certain types of development. Elevation also affects the risk of flooding, with lower-lying areas being more susceptible to inundation during heavy rainfall or storm surges. In some cases, higher elevations may offer scenic views and desirable living conditions, attracting residential development.

RESULTS

Urban Expansion Index (UEI) between 1993 and 2023

The result showed that cities in South-South Nigeria had an exponential increment in urban expansion. Yenagoa had the highest rate of increment in the urban area, increasing from 2% in 1993 to 15% in 2023. Also, Uyo had a very high rate of increment of 358% increasing from 8% to 41% within 30 years. Asaba and Port Harcourt are not left with a high rate of increment as well. This illustrates that cities in the south-south region have undergone rapid urbanisation in the last 30 years due to varying underlying factors. The use of parametric and non-parametric models helped in accurately pointing out how urbanisation had occurred at such a high rate for the region.

Table 2: Urban Area Extent (1993 and 2023)

City	Urban Area % (1993)	Urban Area % (2023)	Rate of Increment (%)
Port Harcourt	10.4837	36.8171	251.17
Uyo	8.98817	41.3033	359.53
Calabar	23.931	35.7934	49.56
Benin City	13.6747	29.2796	113.40
Asaba	8.34694	25.0953	200.63
Yenagoa	2.36166	15.0713	538.10

Parametric and Non-parametric Modeling

Parametric Modeling Results

Linear Regression Model of Urban Expansion

In understanding the key factors that explain urban expansion in the southern region, the model took factors such as topography (elevation, distance to rivers and slope), transport infrastructure (distance to highway and major road) as well as socioeconomic aspects (proximity to markets, ports, and CBD). The linear regression helped in explaining the linear relationship between increasing urban density due to expansion and its influencing factors. Figure 2 reveals a plot showing a linear relationship between actual and predicted urban expansion. Also, Table 3 depicts the relationships between the urban density and its factors with respect to its coefficients. Slope, distance from major roads, distance from river and CBD showed a slightly positive relationship with urban expansion.

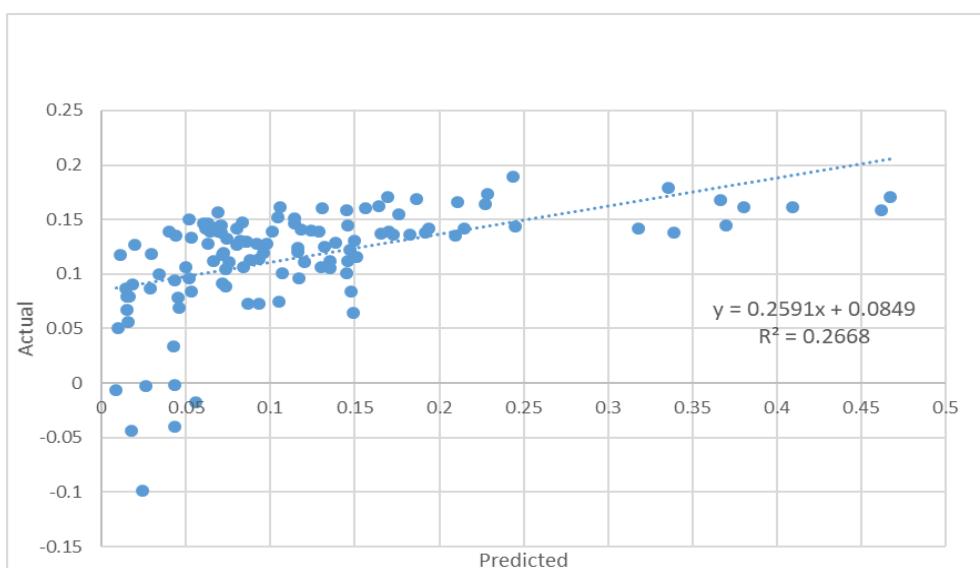


Figure 2: Linear regression plot

Table 3: Coefficient from Linear Regression Model.

Factors	Coefficient	Description
Slope	0.001065	A positive coefficient for slope suggests that areas with steeper slopes are slightly more likely to experience urban expansion. However, the effect is relatively small.
Elevation	-0.00013	A negative coefficient for elevation indicates that higher elevation areas are less likely to experience urban expansion. This suggests a preference for developing low-lying areas.
Major Road Distance	9.83E-07	A very small positive coefficient for distance to major roads suggests a slight tendency for urban expansion to occur further from major roads, possibly reflecting urban sprawl.
Highway Distance	-1.59E-06	A negative coefficient for distance to highways indicates that areas closer to highways are more likely to experience urban expansion, highlighting the importance of accessibility.
River Distance	1.49E-06	A positive coefficient for distance to rivers suggests that urban expansion is slightly more likely to occur further from rivers, possibly due to flood risks or land use regulations
Market Distance	-2.64E-06	A negative coefficient for distance to markets indicates that areas closer to markets are more likely to experience urban expansion, emphasizing the role of economic activities.
CBD Distance	5.37E-07	A small positive coefficient for distance to the Central Business District (CBD) suggests a slight tendency for urban expansion to occur further from the CBD, which could indicate decentralisation or suburbanisation.
Port Distance	-7.25E-07	A negative coefficient for distance to ports indicates that areas closer to ports are more likely to experience urban expansion, reflecting the economic importance of ports.
Mean Squared Error	0.006669	The MSE measures the average squared difference between the observed and predicted values. A lower MSE indicates better model performance. In this case, the MSE is relatively



R² 0.265077

low, suggesting that the model's predictions are reasonably accurate.

An R² of approximately 0.265 indicates that about 26.5% of the variance in urban expansion is explained by the model. While this suggests that the model captures some of the key factors influencing urban expansion, there are likely other factors not included in the model that also play a significant role.

Population growth and industrialisation are major drivers of urban expansion. The positive influence of proximity to markets and ports reflects the economic opportunities that drive urban growth. Also, the slight negative correlation with major road distance may reflect urban sprawl, a phenomenon where urban development spreads outwards along highways rather than concentrating in dense urban centers. This is consistent with findings that transport infrastructure can influence urban growth patterns (Kasraian *et al.*, 2019; Sampson *et al.*, 2021). The negative impact of elevation aligns with studies that show a preference for developing low-lying areas due to factors such as lower construction costs and better accessibility.

Non-Parametric Modeling Results

For a better explanation on the importance of each variable to urban density, the random forest model allowed the modeling of each variable and how important they can be when it comes to predicting urban density. As shown in Figure 3, it was indicated that proximity to port, markets and elevation were the highest important variables contributing to urban density. The R-squared value was 0.6395 which is also higher than the performance value for the logistic model. The mean square error is also 0.00327 which also relatively low. In essence:

- Elevation has the highest importance score, indicating that it is the most influential factor in predicting urban expansion. This suggests that areas with certain elevation levels are more likely to experience urban growth. Typically, lower elevation areas are preferred for development due to easier construction and accessibility.
- The distance to ports is the second most important factor. This highlights the economic significance of ports in driving urban expansion. Areas closer to ports are likely to experience more growth due to the opportunities for trade, commerce, and industry.
- The distance to markets is also a key factor. Markets are central to economic activities, and proximity to markets can attract businesses and residents, leading



to urban growth. This importance score reflects the role of economic hubs in urban development.

- The distance to rivers is another important factor. Rivers provide water resources, transportation routes, and recreational opportunities, making areas near rivers attractive for development. However, flood risks may also influence this relationship.
- Slope has a moderate importance score. Steeper slopes can pose challenges for construction and infrastructure development, making flatter areas more desirable for urban expansion. This score indicates that slope is a consideration but not the most critical factor.

The distance to highways is also a factor in urban expansion. Highways provide essential connectivity and accessibility, facilitating the movement of people and goods. Areas closer to highways are likely to experience more growth, although this score suggests it is less influential than other factors.

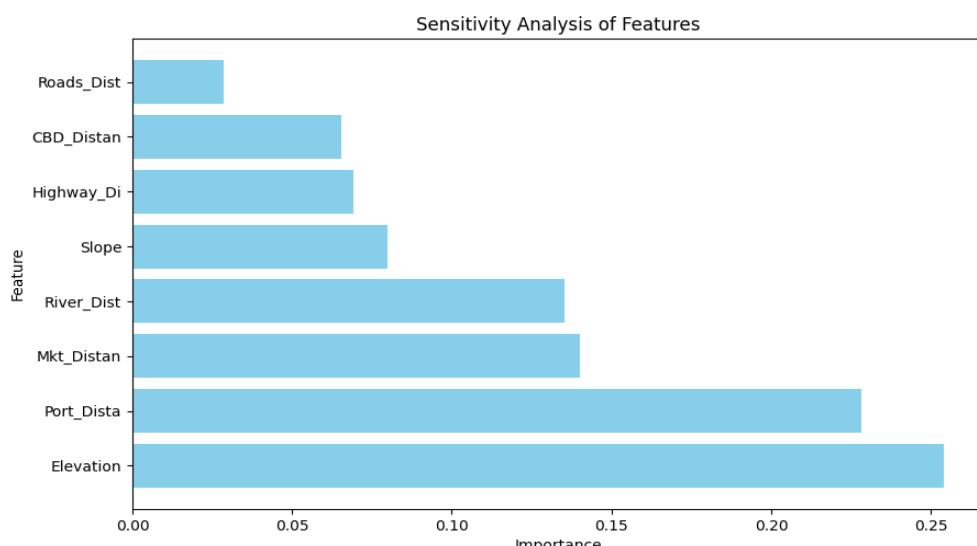


Figure 3: Variables and their importance (RF Modeling)

Comparison of Model Performance

The Random Forest model outperformed the linear regression model in terms of both R-squared and RMSE, indicating its superior ability to capture the complex, non-linear relationships between urban expansion and its driving factors. As shown in the analysis, the RMSE value for linear regression was 0.006669 while for random forest, it was 0.00327 while R-squared was also higher for Random Forest Model (0.6395) than linear regression (0.265077). These results highlight the non-parametric models' superior capability to model complex, non-linear relationships between urban expansion and its

driving factors. Overall, the findings suggest that non-parametric models offer greater predictive power and flexibility in analysing urban expansion dynamics in the South-South region of Nigeria, especially when dealing with heterogeneous and high-dimensional datasets.

DISCUSSION

Effectiveness of Modeling Approaches

Both the parametric (linear regression) and non-parametric (Random Forest) models provided valuable insights into the dynamics of urban expansion in the South-South region. The linear regression model effectively quantified the relationships between urban expansion and key socio-economic and spatial factors, such as population density, distance from major roads, and distance from city centers. However, its ability to capture complex, non-linear relationships was limited (Mostafa et al., 2021).

The Random Forest model, on the other hand, demonstrated a superior capacity to model these complex relationships. Its non-parametric nature allowed it to capture the intricate interactions between various factors influencing urban growth (Shchiptsov et al., 2017). The higher predictive accuracy of the Random Forest model, as indicated by its R-squared and RMSE values, suggests that it is a more robust tool for understanding and predicting urban expansion in this context.

Comparison of Parametric and Non-Parametric Models

Parametric models, like linear regression, offer the advantage of interpretability. The coefficients of the regression model provide clear insights into the direction and magnitude of the relationship between the independent variables and urban expansion. However, they rely on assumptions about the data distribution and the functional form of the relationships, which may not always hold true in complex real-world scenarios (Adepoju et al., 2019).

Non-parametric models, such as Random Forest, are more flexible and can capture complex, non-linear relationships without making strong assumptions about the data. This flexibility often leads to higher predictive accuracy. However, non-parametric models can be more challenging to interpret than parametric models. While variable importance scores provide some insights into the factors driving urban expansion, they do not reveal the precise nature of the relationships (Liu & Li, 2018).

In the context of this study, the trade-off between interpretability and predictive accuracy is evident. If the primary goal is to understand the underlying relationships between urban expansion and its drivers, linear regression can provide valuable insights. However, if the focus is on accurately predicting future urban growth patterns, Random Forest appears to be the more suitable choice.



Factors Driving Urban Expansion in the South-South Region

The models identified several key factors driving urban expansion in the South-South region. These factors can be broadly categorised as:

- A. Accessibility and Connectivity: Distance to highways and major roads significantly influences urban growth. Areas with better road connectivity tend to experience higher rates of urbanisation due to ease of movement and economic activities.
- B. Proximity to Economic Hubs: Distance to the central business district (CBD) and markets are critical factors. Areas closer to the CBD and markets have higher land values and greater access to employment opportunities, services, and amenities, driving both residential and commercial development.
- C. Natural Factors: Slope and elevation play a role in determining the suitability of land for urban development. Gentle slopes and lower elevations are generally more favourable for construction.
- D. Water Access: Distance to rivers influences urban growth, providing opportunities for trade, recreation, and tourism.
- E. Trade and Industry: Proximity to ports drives urban growth by attracting industries related to shipping, logistics, and trade.

Implications for Urban Planning and Policy-Making

The findings of this study have several important implications for urban planning and policy-making in the South-South region:

Sustainable Infrastructure Development: The significant impact of transportation infrastructure (highways, major roads) on urban expansion highlights the need for strategic planning of transportation networks. Investments in road infrastructure should be carefully managed to balance economic development and environmental sustainability.

Economic Development and Land Use Planning: The influence of proximity to CBDs, markets, and ports underscores the importance of integrated land use planning that aligns economic development with spatial growth. Policies should promote efficient land use, reduce urban sprawl, and ensure equitable access to economic opportunities.

Environmental Management: The role of natural factors (slope, elevation, and distance to rivers) in urban expansion emphasises the need for incorporating environmental considerations into urban planning. This includes managing development in areas prone to flooding or with steep slopes, and preserving natural resources and ecosystems.

CONCLUSION

This study examined the application of parametric and non-parametric models in analysing urban expansion in the South-South region of Nigeria. The study showed that urban expansion in the South-South region is driven by a combination of factors, including accessibility and connectivity, proximity to economic hubs, natural factors, water access, and trade and industry.

Both linear regression (parametric) and Random Forest (non-parametric) models provided valuable insights into the dynamics of urban expansion. Linear regression effectively quantified the relationships between urban expansion and key socio-economic and spatial factors, while Random Forest demonstrated superior predictive accuracy due to its ability to capture complex, non-linear relationships. The study also highlighted the importance of considering both the interpretability and predictive accuracy of models when analysing urban expansion. Linear regression offers the advantage of interpretability, while Random Forest excels in predictive performance.

The findings have significant implications for urban planning and policy-making in the South-South region, particularly in the areas of sustainable infrastructure development, economic development and land use planning, environmental management, and data-driven decision-making. This study contributes to the understanding of urban expansion dynamics in a rapidly urbanising region of Nigeria. It demonstrates the value of using both parametric and non-parametric modeling approaches to inform urban planning and policy-making. Future research could explore the use of other advanced modeling techniques, such as deep learning, to further enhance our ability to predict and manage urban growth. Additionally, more detailed studies at the local level could provide further insights into the specific drivers and patterns of urban expansion within different cities and communities in the South-South region.

REFERENCES

Adepoju, K., Adelabu, S. & Fashae, O. (2019). Vegetation Response to Recent Trends in Climate and Land Use Dynamics in a Typical Humid and Dry Tropical Region under Global Change. *Advances in Meteorology*, 2019. <https://doi.org/10.1155/2019/4946127>

Bayode, T. & Siegmund, A. (2023). Tripartite Relationship of Urban Planning, City Growth, and Health for Sustainable Development in Akure, Nigeria. *Frontiers in Sustainable Cities*, 5(January), 1–13. <https://doi.org/10.3389/frsc.2023.1301397>

Girma, B., Shata, B. and Sisay, G. (2022). Factors and actors of urban expansion: The case of Dukem Town, Ethiopia. *European Journal of Sustainable Development Research*, 7(1), em0208. <https://doi.org/10.29333/ejosdr/12591>

Kasraian, D., Maat, K. and van Wee, B. (2019). The impact of urban proximity, transport



accessibility and policy on urban growth: A longitudinal analysis over five decades. *Environment and Planning B: Urban Analytics and City Science*, 46(6), 1000–1017. <https://doi.org/10.1177/2399808317740355>.

Liu, C. & Li, Y. (2018). Spatio-temporal features of urban heat island and its relationship with land use/cover in Mountainous City: A case study in Chongqing. *Sustainability (Switzerland)*, 10(6). <https://doi.org/10.3390/su10061943>

Manesha, E. P. P., Jayasinghe, A. & Kalpana, H. N. (2021). Measuring urban sprawl of small and medium towns using GIS and remote sensing techniques: A case study of Sri Lanka. *Egyptian Journal of Remote Sensing and Space Science*, 24(3P2), 1051–1060. <https://doi.org/10.1016/j.ejrs.2021.11.001>

Mostafa, E., Li, X., Sadek, M. & Dossou, J. F. (2021). Monitoring and forecasting of urban expansion using machine learning-based techniques and remotely sensed data: A case study of Gharbia governorate, Egypt. *Remote Sensing*, 13(22). <https://doi.org/10.3390/rs13224498>

Nayak, M. & Abdullah, T. (2020). Short-term Predication of Risk Management Integrating Artificial Neural Network ANN. *International Journal of Engineering and Advanced Technology*, 9(3), 2828–2833. <https://doi.org/10.35940/ijeat.c5974.029320>

Ocheli, A., Ogbe, O. B. & Aigbadon, G. O. (2021). Geology and geotechnical investigations of part of the Anambra Basin, Southeastern Nigeria: Implications for gully erosion hazards. *Environmental Systems Research*, 10(1). <https://doi.org/10.1186/s40068-021-00228-2>

Otuoze, S. H., Hunt, D. V. L. and Jefferson, I. (2021). Monitoring Spatial-Temporal Transition Dynamics of Transport Infrastructure Space in Urban Growth Phenomena: A Case Study of Lagos—Nigeria. *Frontiers in Future Transportation*, 2(May), 1–19. <https://doi.org/10.3389/ffutr.2021.673110>.

Salam, R. D., Oluwatimilehin, I. A. and Ayanlade, A. (2023). Spatial analysis of urban expansion, land-use dynamics and its effects on land surface temperature in Oyo town, Southwestern Nigeria. *City and Built Environment*, 1(1), 1–18. <https://doi.org/10.1007/s44213-023-00017-w>.

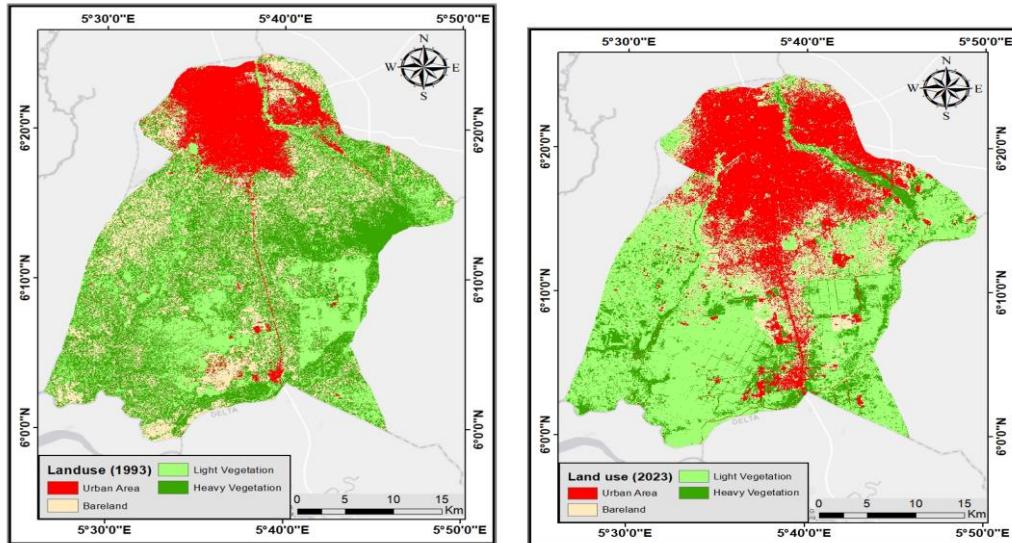
Saleem, S. (2013). Basic of Urban Expansion. *International Journal of Science and Research*, 5(7), 2319–7064. www.ijsr.net.

Sampson, A. P., Weli, V. E., Nwagbara, M. O. and Eludoyin, O. S. (2021). Urban growth dynamics and land use change in Port Harcourt metropolis, Nigeria between 1986 and 2020. *International Journal of Progressive Research in Science and Engineering*, 2(11), 47–56.

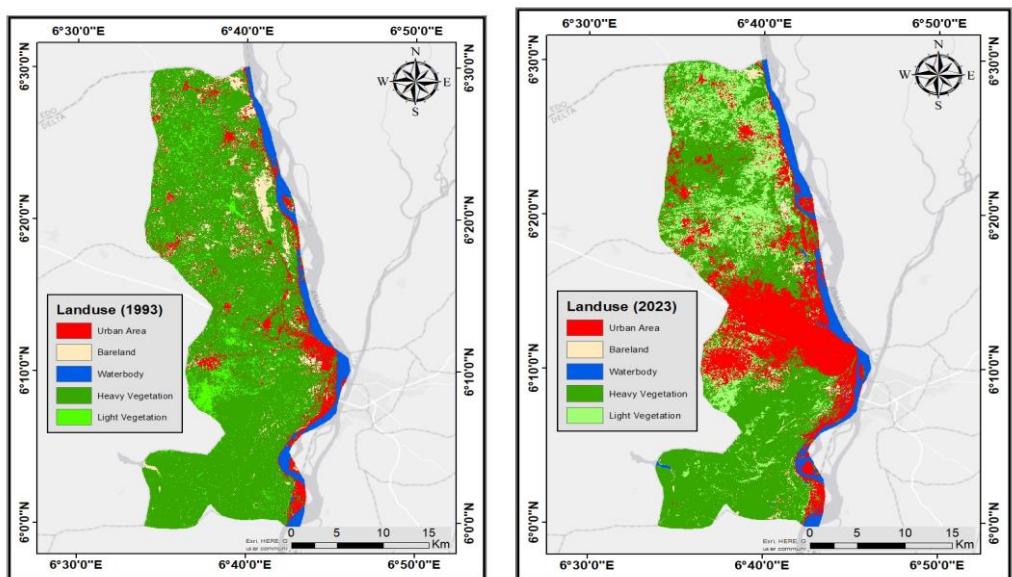
Shchiptsov, A., Hewitt, R. & Rovenskaya, E. (2017). Drivers of urban expansion. *Urban Expansion, Land Cover and Soil Ecosystem Services*, January 2016, 85–119. <https://doi.org/10.4324/9781315715674>.

APPENDICES

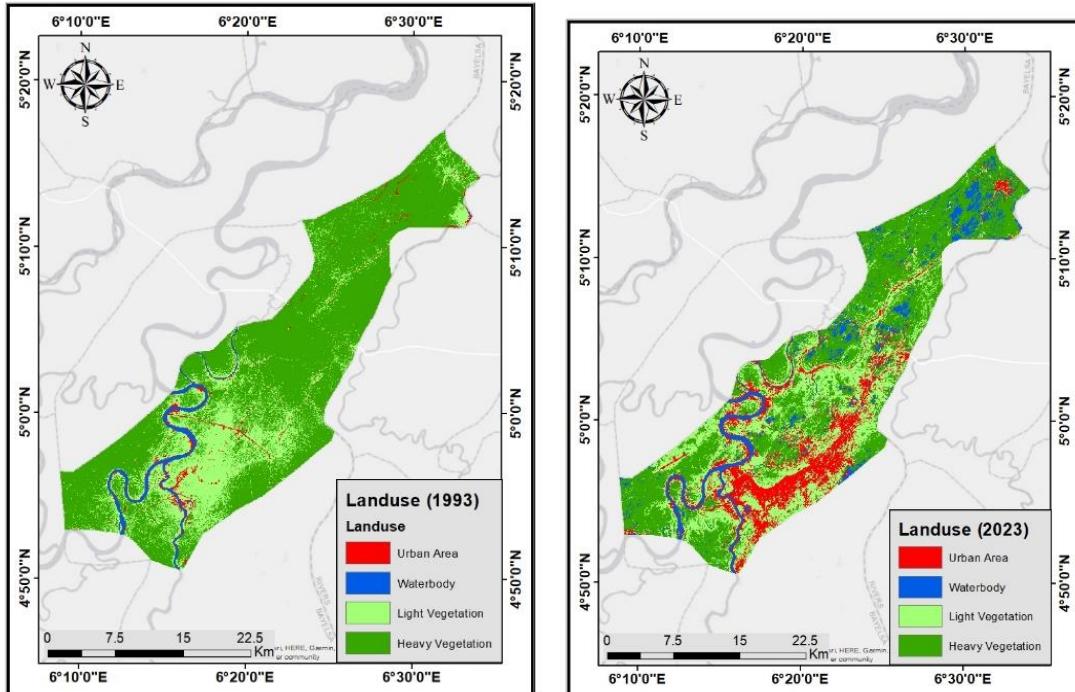
(Land Use Map of South-South Cities and Statistical Assessment of Land Use)



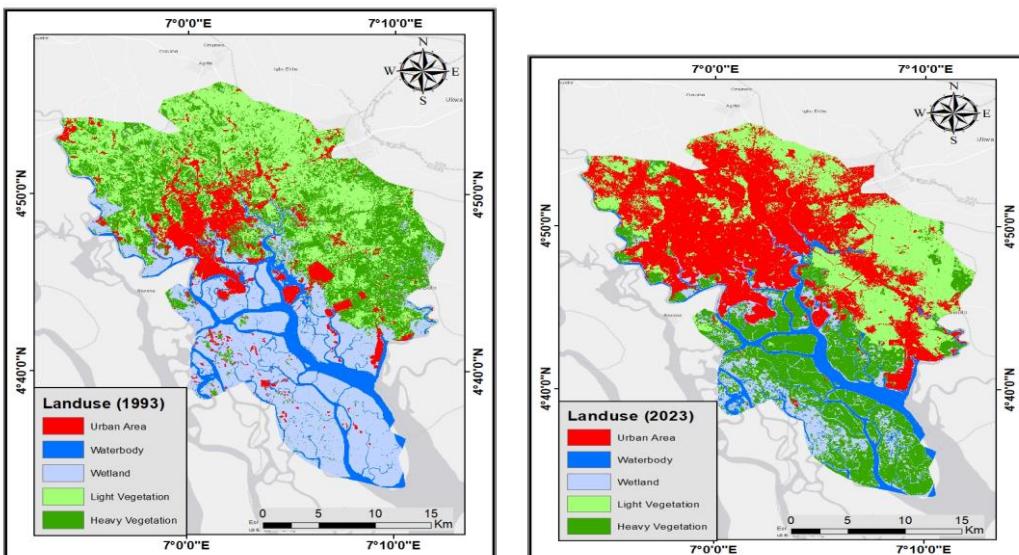
Land use for Benin City (1993 and 2023)



Land use for Asaba (1993 and 2023)

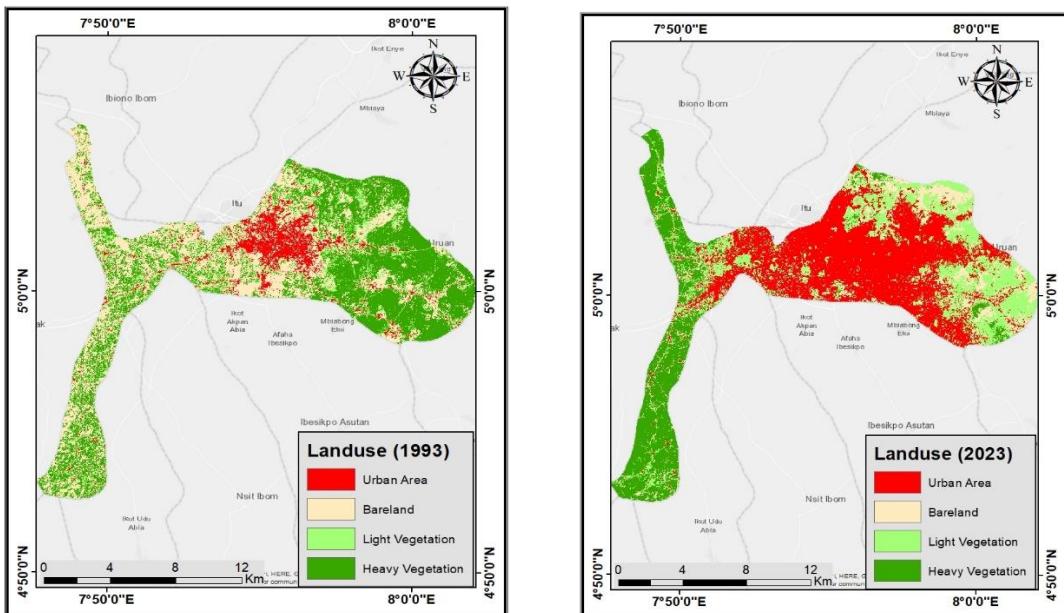


Land use for Benin City and Asaba (1993 and 2023)

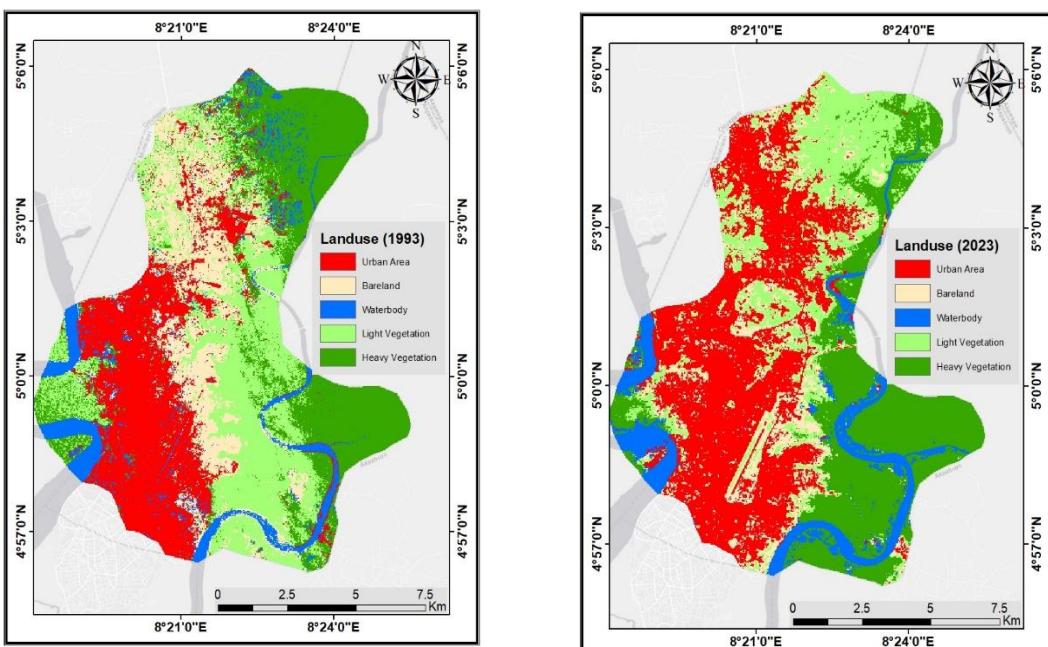


Land Use for Yenagoa City (1993 and 2023)

Land Use for Port Harcourt (1993 and 2023)



Land Use Map of Uyo City (1993 and 2023)



Land Use Map of Calabar City (1993 and 2023)

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Table representing the percentage of each land use type for Port Harcourt across the different years:

Land Use	Percent (1993)	Percent (2023)
Urban Area	10.4837	36.8171
Waterbody	9.09264	8.05935
Wetland	30.5834	9.51143
Light Vegetation	26.1432	23.4945
Heavy Vegetation	23.697	22.1176

Table representing the percentage of each land use type for Uyo

Land Use	Percent (1993)	Percent (2023)
Urban Area	8.98817	41.3033
Bareland	36.5538	12.8444
Light Vegetation	11.0817	24.1095
Heavy Vegetation	43.3763	21.7428

The percentage of each land use type for Calabar

Land Use	Percent (1993)	Percent (2023)
Urban Area	23.931	35.7934
Bareland	17.679	11.3949
Waterbody	8.55207	9.2703
Light Vegetation	24.2845	18.0993
Heavy Vegetation	25.5534	25.4421

Percentage of each land use type for Benin City

Land Use	Percent (1993)	Percent (2023)
Urban Area	13.6747	29.2796
Bareland	23.7695	12.3927
Light Vegetation	23.8522	44.7478
Heavy Vegetation	38.7037	13.5799

Table representing the percentage of each land use type for Asaba

Land Use	Percent (1993)	Percent (2023)
Urban Area	8.34694	25.0953
Bareland	6.45981	3.0028
Waterbody	5.21203	5.46825
Heavy Vegetation	75.4271	49.6326
Light Vegetation	4.55416	16.8008

Table representing the percentage of each land use type for Yenagoa

Land Use	Percent (1993)	Percent (2023)
Urban Area	2.36166	15.0713
Waterbody	2.67348	9.30884
Light Vegetation	24.937	29.7701
Heavy Vegetation	70.0278	45.8498