



---

## Comparative Performance of Selected Machine Learning Algorithms in Predicting Residential Property Price Across Sub-Markets in Lagos Metropolis

Thomas A. Ashaolu<sup>1</sup> (<https://orcid.org/0000-0003-4906-4550>), Amos O. Adewusi<sup>2</sup> (<https://orcid.org/0000-0002-0194-069X>) and Abiodun N. Oyelakin<sup>2</sup> (<https://orcid.org/0000-0002-0194-069X>)

<sup>1</sup> Department of Estate Management, Federal University of Technology, Ilaro, Nigeria

<sup>2</sup> Department of Estate Management, Federal University of Technology, Akure, Nigeria

**To cite this article:** Ashaolu, T.A., Adewusi, A.O. and Oyelakin, A.N. (2026) Comparative Performance of Selected Machine Learning Algorithms in Predicting Residential Property Price Across Sub-Markets in Lagos Metropolis, *Journal of African Real Estate Research*, 11(1), pp. 78-100. DOI: 10.15641/jarer.v11i1.2029

---

### Abstract

Traditional techniques of property valuation are increasingly criticised for their subjectivity, vulnerability to data insufficiency, and other discrepancies, thereby fuelling a methodological shift towards automated and data-driven valuation frameworks. Hence, this study explores three selected machine learning algorithms - Random Forest (RF), Bayesian Ridge (BR), and LASSO Regression – in estimating residential property prices across three distinct sub-markets within Lagos Metropolis. The study seeks to identify the algorithm that achieves the highest predictive precision and to examine the extent to which sub-market heterogeneity affects model reliability. The dataset utilised for the study comprised 469 residential property transactions concluded over the years by thirteen registered Estate Surveying and Valuation firms operating within the Metropolis. The results revealed varied performance across the sub-markets, with Random Forest emerging as the most efficient model, demonstrating the model's robustness and adaptability to nonlinear property data and spatial variability. The Bayesian Ridge Regression model produced moderate results, performing reliably in sub-markets characterised by stable property structures, while LASSO Regression yielded the least accuracy, owing to its sensitivity to linear assumptions and coefficient shrinkage. By situating algorithmic comparison within a spatially segmented urban framework, this research contributes to the development of location-sensitive, data-driven valuation models that can enhance valuation practice, improve investor confidence, and promote greater transparency and efficiency in Nigeria's property market.

---

\*Corresponding author's email address: [Thomas.ashaolu@federalpolyilaro.edu.ng](mailto:Thomas.ashaolu@federalpolyilaro.edu.ng)

©2026 The Author(s). Published by UCT Library. This is an open-access article under the CC BY 4.0 license. <https://creativecommons.org/licenses/by/4>

**Keywords:** *Bayesian Ridge, LASSO Regression, Machine Learning algorithms, Random Forest, Residential Property, Valuation*

## 1. Introduction

Proper valuation remains a central component of investment decisions in real estate. In the residential sector, reliable price estimation is crucial for market stability, as mispricing can distort investment flows, erode investor confidence, and create macroeconomic inefficiencies (Chow and Leung, 2021; Han and Hong, 2023). For emerging markets like Nigeria, the real estate/property market requires reliable valuation to operate transparently and secure investors' confidence. However, traditional valuation techniques, such as the comparative, income, and cost approaches, are increasingly criticised for their subjectivity, reliance on valuers' experience, reliance on inadequate data, and inconsistent selection and adjustment of pertinent variables (Babawale and Ajayi, 2011; Ajibola et al., 2022). Previous studies have expressed concerns about remarkable discrepancies among practitioners when valuing the same property, a phenomenon aptly described as 'valuation variance' (Adewusi, 2024). These discrepancies are part of a broader shift towards automated and data-driven valuation tools, such as machine learning algorithms (MLAs), believed to reduce bias and improve predictive accuracy. Unlike traditional regression models, these MLAs are also expected to provide computational techniques to handle 'complex, nonlinear interactions among property characteristics, locational factors, and socio-economic variables' (Park and Bae, 2022; Peterson and Flanagan, 2023). In fact, researchers appear to be in unison on the capacity of MLAs to outperform conventional econometric models in terms of predictive accuracy, adaptability, and generalisation (Abidoeye and Chan, 2017; Raji et al., 2023; Deng and Zhang, 2025). In the Hong Kong housing market, for instance, Chow and Leung (2021) found that ensemble-based algorithms achieved superior results. Similarly, Han and Hong (2023) concluded that gradient boosting yielded lower mean absolute errors than hedonic regression in Seoul. Peterson and Flanagan (2023) observed that, for the United States and the United Kingdom, ensemble models more effectively captured locational heterogeneity and spatial autocorrelation than traditional linear models. Abidoeye and Chan (2017) and Adewusi (2024) have reported similar improvements, noting that artificial neural networks reduced valuation errors compared to hedonic pricing models and that ML techniques provided more consistent price predictions within Lagos.

In spite of the foregoing, earlier studies had often modelled entire cities as single, uniform markets, regardless of inter-neighbourhood variations in socio-economic or infrastructure parameters (Abidoeye and Chan, 2017; Ajibola et al., 2022; Adewusi, 2024). On the other hand, large cities such as Lagos, London, and Seoul comprise multiple sub-markets with distinct socioeconomic characteristics, land-use structures, and neighbourhood dynamics (Raji et al., 2023; Han and Hong, 2023). Ajayi and Babawale (2011) observed that within Lagos, valuation variance existed in different levels across neighbourhoods, indicating that local context significantly influences price formation.

Recent studies increasingly challenge the homogeneity assumption of urban housing markets, leveraging on urban economic models such as the Bid-Rent Theory (Alonso, 1964) and the Multiple Nuclei Theory (Harris and Ullman, 1945), both of which assert that cities evolve as polycentric systems, each generating distinct rent and price gradients. Empirical research supports these theoretical claims. In the United Kingdom, Orford (2017) demonstrated that London's housing sub-markets responded differently to accessibility and neighbourhood quality. Goodman and Thibodeau (2007) found that price determinants varied significantly between downtown and suburban sub-markets in the United States. In Seoul, South Korea, and Singapore, studies have indicated that ensemble models achieve higher predictive accuracy when trained on localised sub-market data (Park and Bae, 2022; Han and Hong,

2023). These studies confirm that residential property markets exhibit significant spatial heterogeneity requiring explicit modelling for reliable price predictions.

Nigerian studies have not sufficiently explored spatial heterogeneity in valuation frameworks. Though Abidoye and Chan (2017) and Adewusi (2024) confirmed that ML algorithms outperform hedonic and regression-based models, their analyses were conducted using aggregated city-level data. Likewise, Ajibola et al. (2022) and Raji et al. (2023) examined urban housing markets in Lagos without decomposing datasets into income-based or density-based sub-markets. While established valuation literature confirms that property value determinants vary significantly across neighbourhoods (Oyedemi et al., 2018; Oshodi et al., 2020; Ajibola et al., 2022), a few machine learning studies in the Nigerian context have nonetheless employed aggregated, city-level datasets that implicitly obscure these sub-market differences. This study specifically addresses that methodological gap. Meanwhile, Lagos is a mosaic of distinct socio-spatial zones like the high-income Lekki; the mid-income, mixed-use corridor of Ikeja; and the low-income, high-density districts of Mushin–Agege. Each sub-market reflects different combinations of infrastructure, accessibility and neighbourhood amenities that influence price behaviour differently (Adewusi, 2024; Raji et al., 2023). Adopting the same valuation model across varied market environments is tantamount to generating biased estimates and unreliable forecasts. In fact, the heterogeneity of sub-markets aligns with traditional urban theories, which have been acknowledged in emerging discourse, where the accuracy of machine learning algorithms varies across spatial contexts, especially with differences in data density, neighbourhood diversity, and variable interactions (Chow and Leung, 2021; Park and Bae, 2022). The gap identified here is not that researchers have recommended uniform models, but rather that empirical ML valuation studies for Lagos have consistently relied on citywide datasets without submarket stratification. This study addresses this specific and demonstrable methodological absence. Hence, the aim of this study is to examine machine learning performance across multiple sub-markets within Lagos Metropolis.

## 2. Literature Review

### *2.1. Concept of Spatial Heterogeneity and Property Sub-Markets*

In property markets, neighbourhoods exhibit differing characteristics, as reflected in the quality of infrastructure, accessibility, development density, and socio-economic features. Invariably, these exert influence on property pricing. In Lagos, these differences are particularly pronounced due to stark variations in neighbourhood amenities, accessibility, and income levels, leading to significant price disparities among submarkets (Braithwaite, 2007; Jimoh, 2017). Lagos property sub-markets are distinct geographical segments with unique price dynamics, as demonstrated by notable contrasts, such as upscale Lekki having better infrastructure than the more affordable and densely populated Mushin (Jimoh, 2017; Otegbulu, 2017).

Urban economic theories highlight that property prices are influenced by spatial factors rather than being uniform across a city. Alonso's (1964) Bid-Rent Theory posited that property values decline with increasing distance from the city centre due to commuting costs and changes in accessibility. The Multiple Nuclei Theory (Harris and Ullman, 1945) explained that cities have multiple centres, thereby resulting in varying price gradients. Empirical evidence from Lagos supports these frameworks, showing that neighbourhood characteristics and proximity to key services significantly affect prices (Braithwaite, 2007; Aliu, 2014).

It is important to note that machine learning algorithms, as adopted in this study, are primarily instruments of mass valuation (also known as Automated Valuation Models, or AVMs), rather than tools for appraising individual properties in the manner of traditional single-property valuation. Numerous studies have established the applicability of ML in mass valuation systems. Antipov and Pokryshevskaya (2012), McCluskey et al. (2013), and Peterson and Flanagan (2023) demonstrated that ensemble and regression-based models are well-suited to large-scale, data-driven appraisal. This study is situated within a mass valuation framework, which is particularly relevant for policy-making, investment analysis, and taxation purposes in emerging markets like Nigeria.

## ***2.2. Conventional Pricing Methodology and Valuation Inaccuracy***

Traditional valuation methodologies will often be challenged by heterogeneous markets like Lagos. The effectiveness of the Comparative Method to leverage on the similarity of property variables is often compromised by the apparently subtle yet potent differences in property features within small geographic areas, and these often lead to valuation discrepancies (Jimoh, 2017). The income Capitalisation Method capitalises future income streams but struggles with the reliability of rental income and yield in areas with fluctuating demand, while the Cost Approach is limited by difficulties in estimating replacement costs and accounting for location-driven demand variations (Otegbulu, 2017).

These traditional methods frequently lead to valuation inconsistencies with different valuers providing varying estimates for the same property, thereby undermining trust in the valuation process. The result is a shift towards more data-driven approaches, such as machine learning algorithms believed to incorporate localised market conditions, yielding more accurate, consistent results across sub-markets (Jimoh, 2017).

## ***2.3. Machine Learning Algorithms and Property Price Accuracy***

Machine learning algorithms offer promising alternatives to traditional property valuation models by modelling complex, non-linear interactions among property features, socio-economic factors, and spatial location. Algorithms like Random Forest (RF), Bayesian Ridge Regression (BR), and LASSO Regression have demonstrated their effectiveness in property price prediction by capturing interactions among variables that traditional methods often overlook (Breiman, 2001; Zurada et al., 2011; Antipov and Pokryshevskaya, 2012; Abidoeye and Chan, 2017; Hong et al., 2020; Chow and Leung, 2021; Park and Bae, 2022; Han and Hong, 2023; Raji et al., 2023). Therefore, they often perform better than conventional models in terms of predictive accuracy and capacity to manage the large dimensionality of real estate data. Also, ML methods will result in substantial advancements in valuation accuracy, which is essential to market transparency and investor confidence.

# **3. Methodology**

## ***3.1. Input Variables and Data Samples***

The dataset used in this research included a total of 469 residential property transactions with conclusive history, from thirteen registered firms of Estate Surveyors and Valuers in Lagos Metropolis. The official directory of the Nigerian Institution of Estate Surveyors and Valuers (NIESV, 2024) was used to verify these firms, ensuring the data was authentic and reliable. Lagos was chosen as the study location because it is Nigeria's most active and heterogeneous property market, with a variety of socio-economic, infrastructural, and environmental characteristics that affect housing prices. The data set was rather broad in its property features – number of bedrooms, bathrooms, toilets, and floors; age and condition;

environmental and neighbourhood character; and proximity to facilities. These were important variables that determined residential property prices and were used as inputs to the machine-learning models.

To capture the heterogeneity in the market, three different sub-markets, with striking socio-economic and spatial settings, were identified within Lagos Metropolis, comprising Lekki, Ikeja, and Mushin-Agege. Lekki is a high-income waterfront corridor dominated by luxury housing developments. Ikeja is a typical mid-income mixed-use mainland district integrating commercial and residential functions, while Mushin–Agege represents the low-income, high-density zone characterised by informal housing and infrastructure deficits. The stratification enabled this study of algorithmic performance in residential settings to display the contrasts that highlight local dynamics in property valuation. Before analysis, all transaction prices were log-transformed to address data skewness and ensure normality of the distribution. Continuous-type variables were normalised using z-score normalisation to bring all variables to a comparable scale. Categorical variables were converted to numeric codes for model training, e.g., property type and finishing materials. Interquartile Range (IQR) and mean substitution were used to handle outliers and missing values, respectively, to maintain dataset integrity. Thereafter, the data were divided into sub-market-specific subsets of 182, 153, and 134 records from Lekki, Ikeja, and Mushin-Agege, respectively. This ensured that each segment of the housing market is sufficiently represented in the data for model calibration and comparison with other housing markets.

### ***3.2. Operationalisation of Variables***

To facilitate model development and ensure consistency in analysis, the study identified and operationalised the key variables influencing residential property prices across the selected sub-markets. The dependent variable in the analysis is the actual property selling price. This represents the response variable being predicted by the machine-learning algorithms. The independent variables comprise structural, locational, and environmental attributes commonly recognised in the valuation and hedonic modelling literature as significant determinants of housing value (Abidoye and Chan, 2017; Ajibola et al., 2022; Raji et al., 2023).

Each variable was assigned a unique code and unit of measurement to ensure uniformity across all sub-markets and facilitate efficient model training. Attributes like the number of bedrooms, bathrooms, toilets, floors, and property size described the physical structure of each residential unit. The accessibility advantages were measured by proximity to schools, hospitals, and shopping centres, while qualitative differences in property desirability were defined by environmental and neighbourhood indicators, including security features and the condition of facilities. Categorical variables were encoded numerically, whereas continuous attributes were measured using actual figures derived from the transaction data. The operationalised variables are presented in Table 1.

### ***3.3. Machine Learning Algorithms***

This research used three machine learning algorithms – Random Forest (RF), Bayesian Ridge Regression (BR), and Least Absolute Shrinkage and Selection Operator (LASSO)- to forecast the prices of residential properties in the sub-markets of the Lagos Metropolis. The algorithms were chosen because they have good balancing, predictive accuracy, interpretability, and robustness in modelling heterogeneous property markets (Breiman, 2001; MacKay, 1992; Tibshirani, 1996; Hong et al., 2020; Efron et al., 2004).

**Table 1: Operationalisation of Variables**

Variable	Variable Code	Measurement/Description
<b>Dependent Variable</b>		
Property Price	Pptyprice	Actual selling price of the property (₦, logtransformed)
<b>Independent Variables</b>		
Property Size	Pptysize	Floor area of the property (m <sup>2</sup> )
Number of Bedrooms	No_bed	Actual number of bedrooms
Number of Bathrooms	No_bath	Actual number of bathrooms
Number of Toilets	No_toilet	Actual number of toilets
Number of Floors	No_floors	Actual number of floors
Property Type	Pptytype	1 = Detached, 2 = Semi-detached, 3 = Duplex, 4 = Flat
Age of Property	Pptyage	Age in years
Security Provision	Sect	1 = Electric Fence, 2 = CCTV, 3 = Gate
Living Room Size	Livngrm	1 = Large, 2 = Small
Condition of Property	Condt	1 = Poor, 2 = Fair, 3 = Good
Parking Space	Carpark	Number of available parking lots
Location Density	Lctn	1 = Low, 2 = Medium, 3 = High
Access to Shopping Malls	Accessshop	1 = Close, 2 = Distant
Access to Schools	Accessschool	1 = Close, 2 = Distant
Access to Hospitals	Accesshop	1 = Close, 2 = Distant
Access to Restaurants	Accessrest	1 = Close, 2 = Distant
Roof Type	Roof	1 = Gerrard, 2 = Long Span, 3 = Corrugated
Floor Finish	Floorfinish	1 = Ceramic Tiles, 2 = Wooden Floor, 3 = Granite/Marble
Ceiling Type	Ceilg	1 = POP, 2 = PVC, 3 = Asbestos
Type of Painting	Paintg	1 = Satin, 2 = Emulsion, 3 = Textcote
Type of Window	Windw	1 = Glazed Aluminum, 2 = Louvres
Boys' Quarters	Boysq	1 = Present, 0 = Not Present
Door Type	Door	1 = Panel, 2 = Metal, 3 = Flush
Condition of Facilities	Fact	1 = Poor, 2 = Fair, 3 = Good

Source: Field Survey, 2025

### 3.3.1. Random Forest (RF)

The Random Forest algorithm, proposed by Breiman (2001), is an ensemble learning method that builds several decision trees on bootstrap samples of the training data and randomly selects features at each split node. The average of the three outputs represents the final prediction, thereby minimising model variation and avoiding over-fitting. In real estate valuation, Random Forest is highly effective for modelling complex, nonlinear correlations among property characteristics, location, and market forces, without a rigid set of parametric assumptions (Hong, Kim, and Lee, 2020). Its internal feature-importance metric helps identify the most significant determinants of property prices, making it accurate and interpretable for practical valuation.

**3.3.2. Bayesian Ridge Regression (BR)**

Bayesian Ridge Regression was formulated by MacKay (1992) and subsequently broadened by Tipping and Bishop (2007). It is a linear regression method that uses a Bayesian prior over the regression coefficients, thus providing a built-in regularisation effect. This probabilistic framework estimates a posterior distribution over model parameters and incorporates uncertainty in coefficient estimation. For real-estate data—where multi-collinearity often arises among structural and neighbourhood features—Bayesian Ridge provides stable estimates and reduces over-fitting by penalising extreme coefficient values. It also generates predictive intervals that quantify the confidence level around price estimates, a quality particularly valuable in data-driven property appraisal (Tipping and Bishop, 2007).

**3.3.3. Least Absolute Shrinkage and Selection Operator (LASSO)**

The LASSO model, proposed by Tibshirani (1996), improves the traditional regression model by adding an L1-norm penalty to the regression coefficients. This constraint forces reduce influential variables toward zero, enabling automatic variable selection while controlling model complexity. LASSO has been popular in property valuation and spatial-econometric research for isolating the strongest predictors of housing prices, including building size, condition, and accessibility (Efron et al., 2004; Peterson and Flanagan, 2023). Although it assumes linear relationships between the predictors, it offers good interpretability and variable-selection ability, making it a robust tool for comparing nonlinear and ensemble models.

Despite Random Forest, Bayesian Ridge and LASSO methodological diversity, they are complementary modelling frameworks for use in property valuation. Random Forest can capture nonlinearities and complex interaction effects; Bayesian Ridge provides probabilistic regularisation and uncertainty quantification; while LASSO provides parsimony and interpretability through sparse coefficient estimation. Previous empirical studies supported this: Breiman (2001) and Hong et al. (2020) reported higher predictive accuracy of Random Forest model in a heterogeneous housing market; MacKay (1992) and Tipping and Bishop (2007) posited that Bayesian Ridge offers a good solution to over-fitting and multi-collinearity, while LASSO was demonstrated by Tibshirani (1996) and Efron et al. (2004) to be capable of identifying significant determinants of price among high-dimensional datasets. Integrating these algorithms allows this study to balance interpretability and predictive performance—ensuring both academic rigour and practical relevance in modelling real-estate market behaviour (Peterson and Flanagan, 2023).

**3.4. Performance Metrics**

The literature has many predictive accuracy measures. However, the suitability of each depends on the purpose at hand. To evaluate and compare the predictive performance of the chosen machine learning algorithms, four statistics were used in this paper. They are Coefficient of Determination (R<sup>2</sup>), Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). These performance measures have been widely used in previous valuation and predictive modelling studies (Zurada et al., 2011; McCluskey et al., 2013; Han and Hong, 2023; Raji et al., 2023), and are expressed in mathematical equations (1) to (4) below:

$$r^2 = 1 - \frac{\sum_{i=1}^n (P_i - P'_i)^2}{\sum_{i=1}^n (P_i - \bar{P})^2} \text{----- (1)}$$

$$MAE = \frac{1}{n} \sum_{i=1}^n (P_i - P'_i) \text{----- (2)}$$

$$MAPE = \frac{\sum_{i=1}^n \left( \frac{P_i - P'_i}{P_i} \right)}{n} \times 100 \text{ ----- (3)}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^n (P_i - P'_i)^2} \text{ ----- (4)}$$

where (P<sub>i</sub>) represents the actual market value of each property, (P'<sub>i</sub>) is the predicted value obtained from the model, ( $\bar{P}$ ) denotes the mean of the observed prices, and (n) is the number of observations. R<sup>2</sup> stands for the proportion of variance in property prices explained by the predictor model, MAE for the average and RMSE for the squared deviations between the predicted and observed prices. The MAPE is the mean absolute deviation, as a percentage of the actual price values. Hence, the higher the R<sup>2</sup>, the stronger the variance explained and the model reliability. A good predictive accuracy is indicated by lower values of MAE, RMSE, and MAPE. Combining these measures ensures that across the three sub-markets, there is effective comparative analysis of the accuracy and robustness of the four selected algorithms-Random Forest, XGBoost, SVR, and LASSO.

### 3.5. Model Development and Specification

#### 3.5.1. Training Data

The model development stage used the pre-processed dataset of 469 residential property transactions across the Lekki, Ikeja, and Mushin–Agege sub-markets of Lagos Metropolis, as obtained from registered estate firms. Data was randomly split into training and testing subsets, with a typical 80/20 scale to achieve model generalisability and reduce over-fitting (Can et al., 2019; Kuhn and Johnson, 2013). Model training was allotted 80 per cent (80%) of the data, and the algorithms – Random Forest (RF), Bayesian Ridge Regression (BR), and LASSO – were trained to learn the intricate patterns and connections between the dependent variable (log-transformed property prices) and the independent variables (structural, locational, and neighbourhood characteristics). The other 20% of the data was set aside to test and validate the model, to avoid bias in performance analysis.

During training, hyperparameter tuning was performed to optimise each algorithm’s performance using iterative search procedures. For Random Forest, the number of trees, depth, and minimum samples per split were optimised; for Bayesian Ridge, the priors and regularisation parameters were calibrated; while for LASSO, the alpha penalty term was selected using cross-validation. These adjustments improved the stability and predictive consistency of each model across all three sub-markets.

#### 3.5.2. Test Data

To achieve generalisation without bias to the training sample, test data were used to assess model performance in actual predictive conditions. Like Can et al. (2019) and Kuhn and Johnson (2013), the model was evaluated by comparing the actual and predicted log-transformed market values. This step was necessary to measure the degree to which each algorithm could recreate observed price dynamics on unobservable property deals in the three market clusters – Lekki, Ikeja and Mushin-Agege.

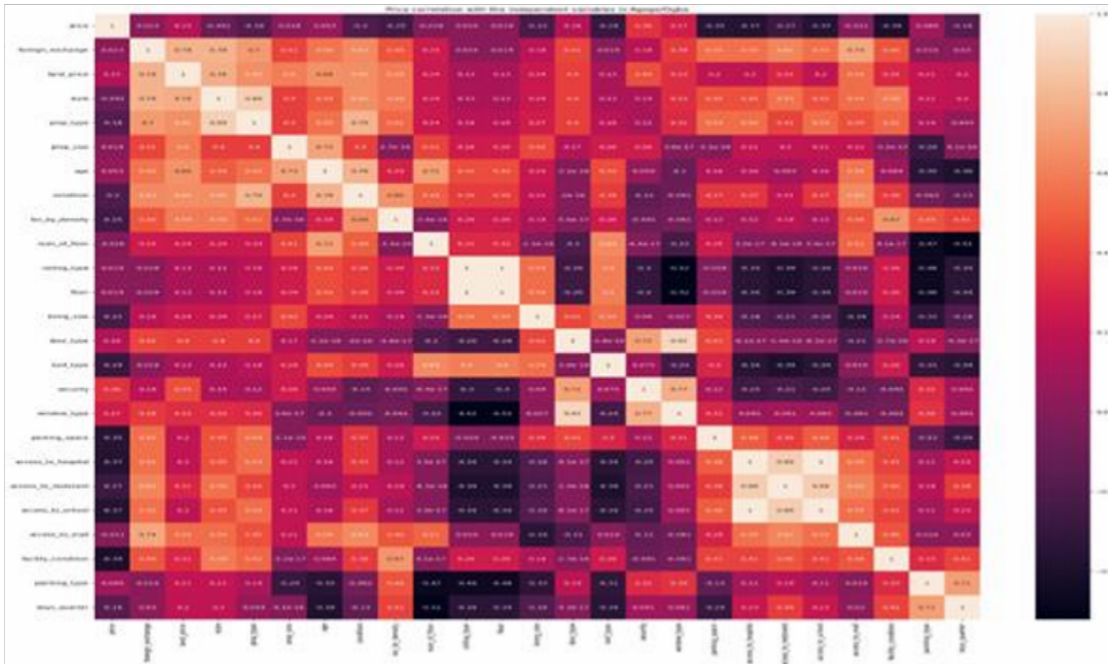
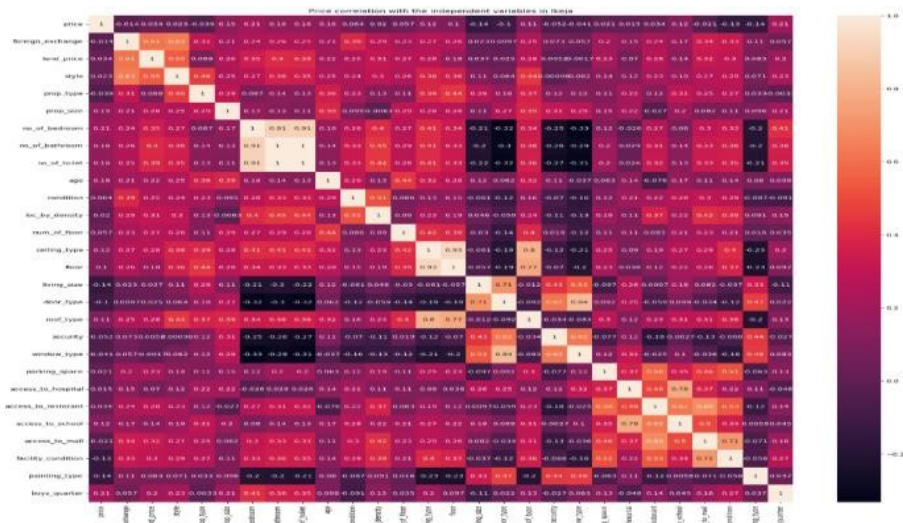
## 4. Results and Discussion

### 4.1. Descriptive Statistics of Property Attributes

Table 2 (in the Appendix) summarises the descriptive statistics of major explanatory variables, including the number of bedrooms, bathrooms, property age, condition, parking availability, and market



1b: Ikeja Sub-market



1c: Mushin-Age Submarket

Figure 1a-c: Variable correlation structure across the three Sub-markets

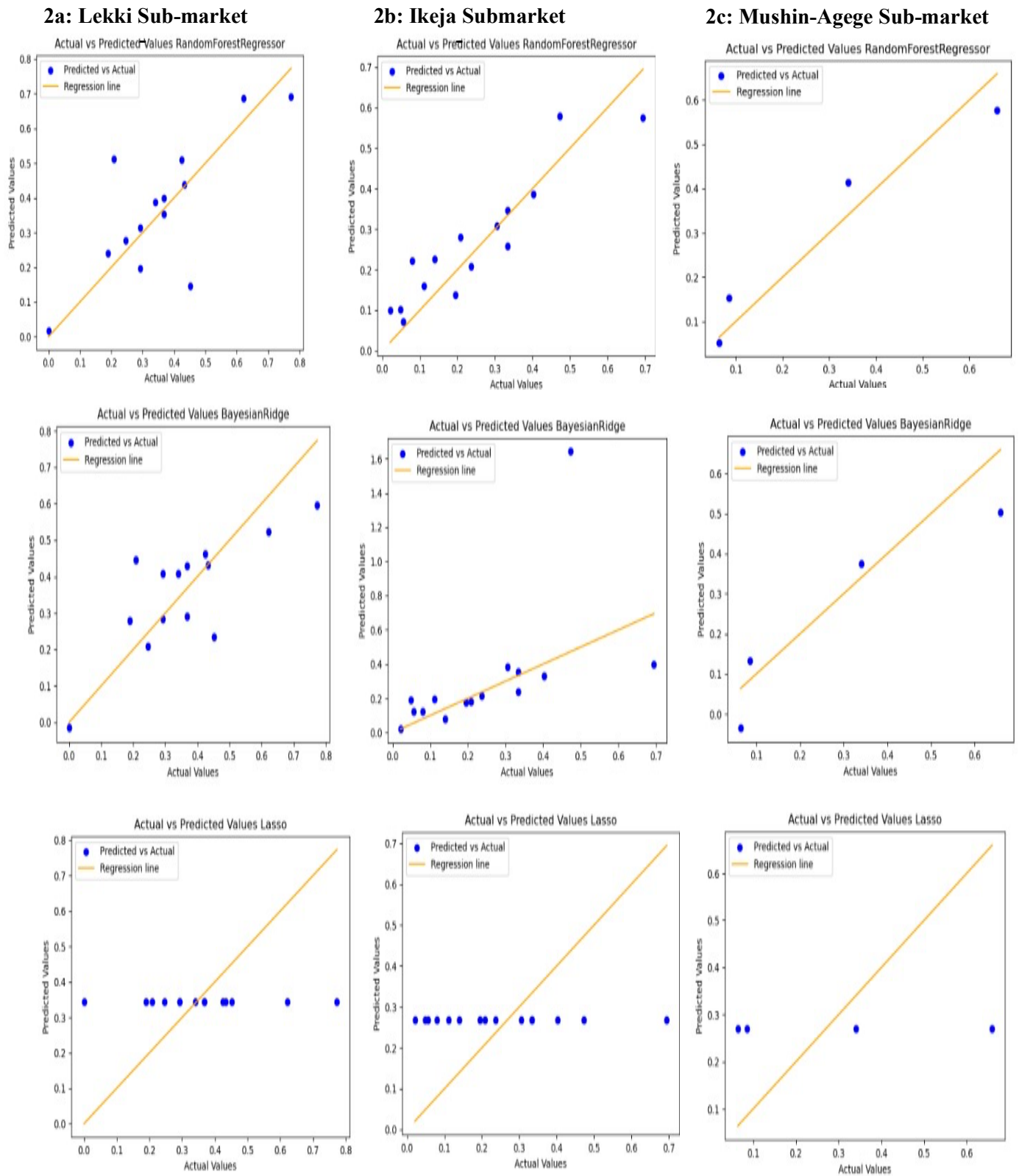
Source: Field Survey, 2025

### 4.3. Visual Assessment of Model Performance

The scatter plots of actual versus predicted prices were examined to provide a visual evaluation of model accuracy. Across the three sub-markets, as indicated in Figure 2a–c, the plots showed that Random Forest achieved the tightest alignment along the 45° reference line, indicating the highest correspondence between predicted and actual market values. Bayesian Ridge Regression produced balanced predictions with moderate residual spread, while LASSO showed slightly greater dispersion

at higher price levels, especially in the Mushin–Agege sub-market (Fig. 2c). These visual results collectively suggest that ensemble and regularised regression methods captured both the linear and nonlinear components of Lagos’ property market behaviour.

The scatter plots for the Lekki sub-market in Figure 2a illustrate a strong positive correlation between actual and predicted prices for all three algorithms. Random Forest exhibited the tightest alignment along the 45° line, indicating minimal residual dispersion.



**Fig. 2a–c: Scatter plots showing the relationship between actual and predicted log property prices for the three sub-markets and across the three models**

Source: Field Survey, 2025

LASSO and Bayesian Ridge also performed consistently with moderate deviations at higher price ranges. The result confirms that ensemble and regularised linear models effectively capture price heterogeneity within Lekki’s luxury residential market. In the Ikeja sub-market (Figure 2b), all models recorded strong predictive fits, though Random Forest again displayed superior consistency. Bayesian Ridge maintained a smooth prediction pattern with fewer outliers, while LASSO’s performance was slightly constrained by its linear assumption. The plots demonstrate the models’ ability to generalise across mid-income neighbourhoods that exhibit both residential and commercial property interactions. The Mushin–Agege sub-market (Figure 2c) exhibited greater price variability, as reflected by a wider spread of points around the regression line. Random Forest provided the most accurate estimates for this low-income, high-density zone, where irregular housing characteristics and infrastructure deficiencies tend to introduce data noise. LASSO and Bayesian Ridge under-predicted some outliers, suggesting limited adaptability to extreme values, yet still achieved acceptable correlation strength across the sample.

Across the three sub-markets, the scatter plot analysis confirms that the Random Forest algorithm consistently outperformed the linear-based models in reproducing market prices. This aligns with findings by Hong et al. (2020) and Peterson and Flanagan (2023), who reported that ensemble-based learners excelled in modelling complex housing attributes. Nonetheless, Bayesian Ridge and LASSO provided valuable interpretive power and computational efficiency, making them suitable for transparent appraisal contexts. The convergence observed across the models indicates a strong predictive relationship between the estimated and actual values, validating the reliability of the training and testing procedure.

#### 4.4. Quantitative Model Evaluation and Comparison

Table 3 presents the comparative performance of the three algorithms across the three sub-markets. The performance was assessed using both training and testing results of the coefficient of determination ( $R^2$ ), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). The inclusion of both training and testing phases provides a comprehensive insight into model generalisation, highlighting the ability of each algorithm to learn effectively without over-fitting or under-fitting the dataset.

**Table 3: Quantitative Model Evaluation and Comparison**

Algorithms	Sub-Market	R2	MAE	MAPE	RMSE	R <sup>2</sup>	MAE	MAPE	RMSE
Random	Lekki	0.95	0.03	0.22	0.04	0.54	0.08	0.37	0.11
	Ikeja	0.93	0.03	0.19	0.04	0.74	0.06	0.29	0.07
	Muishin-Agege	0.95	0.04	0.86	0.05	0.90	0.06	0.25	0.06
Bayesian	Lekki	0.75	0.08	0.53	0.10	0.41	0.09	0.32	0.11
	Ikeja	0.61	0.07	0.84	0.10	0.27	0.15	0.37	0.31
	Mushin-Agege	0.76	0.09	0.77	0.12	0.78	0.08	0.89	0.09
LASSO	Lekki	0.01	0.17	0.38	0.09	0.10	0.13	0.39	0.18
	Ikeja	0.11	0.12	0.19	0.16	0.02	0.15	0.56	0.18
	Mushin-Agege	0.01	0.20	0.69	0.25	0.27	0.21	0.79	0.24

Source: Field Survey, 2025

As revealed in Table 3, Random Forest attained a training  $R^2$  of 0.95 and a testing  $R^2$  of 0.54 for Lekki, demonstrating a reasonable generalisation performance despite the high structural and price variability typical of luxury sub-markets. The relatively moderate test accuracy in Lekki can be attributed to the heterogeneous nature of the area, where property values vary sharply based on location, building style, and infrastructure development. Conversely, in Ikeja, Random Forest achieved a higher testing  $R^2$  of 0.74, alongside lower RMSE (0.073) and MAPE (0.29), indicating greater model stability and predictive precision within this mid-income, mixed-use submarket. The algorithm recorded its best performance in Mushin–Agege, where both training and testing  $R^2$  values reached 0.95 and 0.90, respectively, supported by the lowest RMSE (0.065) and MAPE (0.25). This superior accuracy can be attributed to the more uniform property characteristics in this low-income market segment, allowing the ensemble method to capture patterns effectively.

The Bayesian Ridge Regression model produced moderate results across the sub-markets, reflecting the strength of its probabilistic regularisation framework in handling collinear variables while maintaining computational simplicity. In Lekki, it achieved a training  $R^2$  of 0.75 and a testing  $R^2$  of 0.41, indicating a reasonable but less stable fit compared to Random Forest. In Ikeja, the testing  $R^2$  declined further to 0.27, suggesting a limited ability to accommodate the nonlinear market relationships within this submarket. However, in Mushin–Agege, the model showed improved adaptability with a testing  $R^2$  of 0.78 and relatively low RMSE (0.098), confirming its potential efficiency in more homogeneous data environments. These outcomes align with MacKay (1992) and Tipping and Bishop (2007), who highlighted that Bayesian models tend to perform more reliably in structured and less complex datasets. LASSO Regression model, on the other hand, exhibited the weakest performance across all sub-markets, reflecting its sensitivity to feature-scarcity and linear assumptions. The testing  $R^2$  values ranged from 0.10 in Lekki to 0.79 in Mushin–Agege, accompanied by higher RMSE and MAPE scores. This pattern suggests that while LASSO effectively performs variable selection and prevents overfitting through coefficient shrinkage, it may not sufficiently capture the nonlinear relationships inherent in property price dynamics, especially in submarkets characterised by luxury diversity and infrastructure-driven price fluctuations. Nevertheless, LASSO remains valuable for interpretability and feature reduction, making it useful in exploratory modelling and variable importance assessment, as supported by Tibshirani (1996) and Efron et al. (2004).

Overall, the results indicate that Random Forest produced the most accurate, consistent, and generalisable predictions across the study area. The model's ensemble learning mechanism, which aggregates multiple decision trees to reduce variance and bias, enables it to capture complex interactions between property attributes and market behaviour more effectively than linear-based models. The dominance of Random Forest in this analysis corroborates the findings of Breiman (2001), Hong et al. (2020), and Peterson and Flanagan (2023), who established that tree-based ensemble methods outperform single-estimator models in real estate valuation tasks. The relatively modest performance of Bayesian Ridge and LASSO further reinforces the notion that while regularisation-based methods enhance interpretability, their linear frameworks limit their ability to fully represent the nonlinear spatial and locational dynamics of property markets. Across sub-markets, predictive accuracy followed the order Mushin–Agege > Ikeja > Lekki. This progression reflects the interplay between data consistency and market complexity. Mushin–Agege's stable housing typologies allowed for stronger model learning, whereas Lekki's high-end, spatially diverse market introduced greater variability and potential noise in property prices. The findings affirm that integrating ensemble algorithms such as Random Forest with regularised regression models like Bayesian Ridge and LASSO provides a balanced methodological framework for achieving both predictive accuracy and model transparency in the valuation of residential properties across heterogeneous urban sub-markets, as no single algorithm

performs optimally across all contexts. Rather, model efficiency is inherently dependent on data quality and the structural composition of each market segment.

#### ***4.5. The Alignment Between Study Findings and Existing Literature***

The findings of this study provide valuable insights into the comparative efficiency of different machine learning algorithms in predicting residential property prices across the heterogeneous sub-markets of Lagos Metropolis. The consistent superiority of the Random Forest algorithm across the three sub-markets highlights the effectiveness of ensemble learning techniques in handling nonlinear relationships, high-dimensional data, and multi-collinearity problems commonly encountered in property valuation datasets. The model's robust performance is in line with the works of Breiman (2001), Hong et al. (2020), and Peterson and Flanagan (2023), who observed that Random Forest and other ensemble-based models outperform conventional and single regressor techniques in housing market analysis due to their ability to model complex interactions among structural and location variables.

The relatively high predictive accuracy observed in the Mushin–Agege sub-market suggests that Random Forest performs particularly well in environments where property attributes exhibit less variability. This finding aligns with Han and Hong (2023), who observed that ensemble models achieve optimal generalisation in stable and structured housing datasets. Conversely, the slightly lower  $R^2$  and higher error metrics obtained in Lekki reflect the challenges posed by heterogeneous and high-value sub-markets, where spatial differentiation, architectural diversity, and infrastructure disparities introduce additional prediction complexity. Such variability is consistent with Can et al. (2019), who emphasised that model performance declines in luxury property clusters characterised by market segmentation and price volatility.

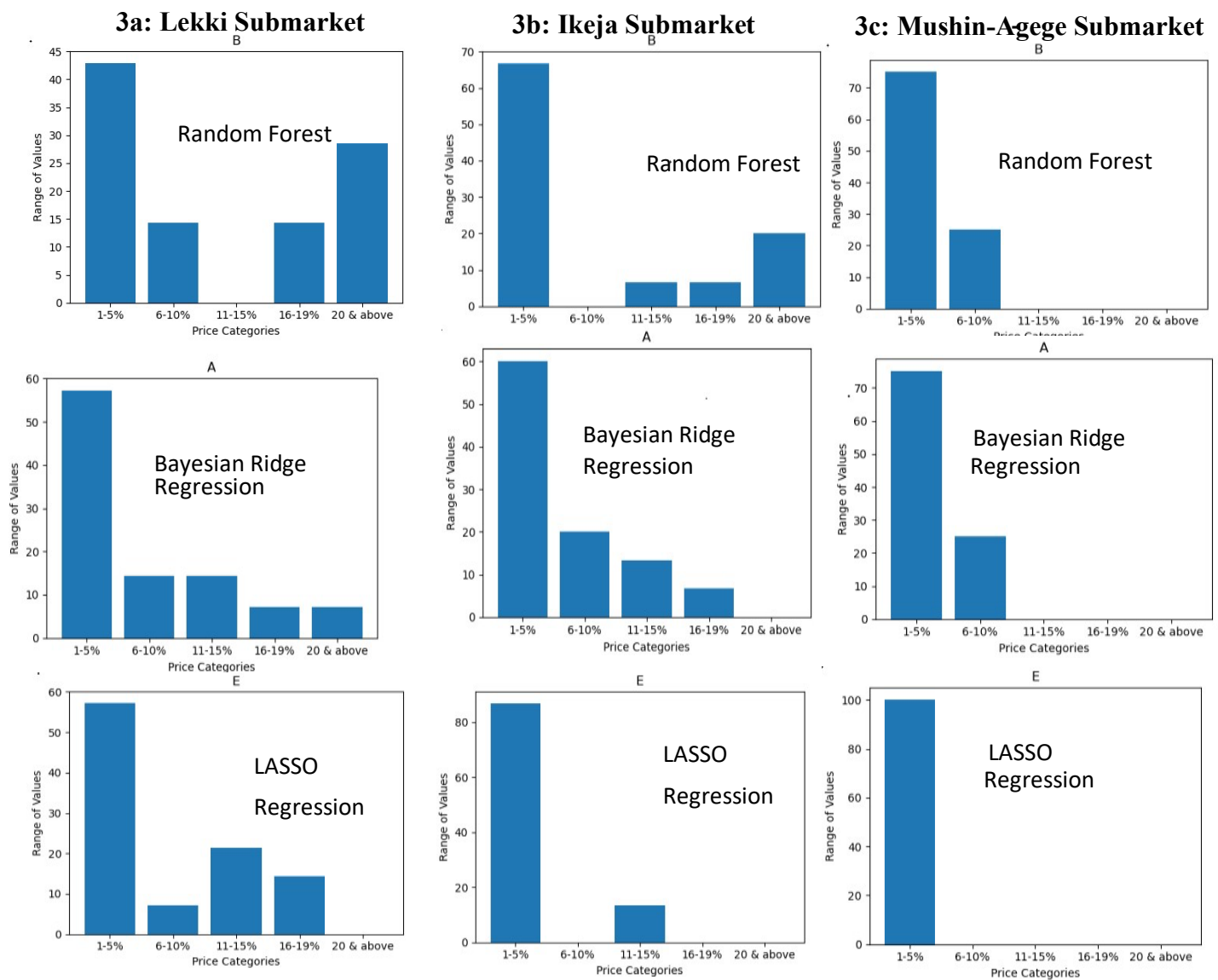
The Bayesian Ridge Regression model exhibited moderate yet stable performance, demonstrating that probabilistic regularisation techniques remain valuable for ensuring model interpretability and controlling coefficient shrinkage. The findings correspond with those of MacKay (1992) and Tipping and Bishop (2007), who established that Bayesian frameworks improve estimation reliability, especially in datasets affected by multicollinearity. Its relatively lower predictive power in Lekki and Ikeja underscores the model's limitation in fully capturing nonlinear relationships, but its balanced trade-off between simplicity and robustness makes it suitable for structured valuation tasks and policy-oriented analyses.

The LASSO Regression model produced the weakest predictive outcomes, with significantly lower  $R^2$  values and higher error rates across the sub-markets. This is consistent with Tibshirani (1996) and Efron et al. (2004), who observed that while LASSO performs effective variable selection and improves model parsimony, it tends to oversimplify relationships in datasets governed by complex interactions. Despite its lower predictive accuracy, the LASSO model's strength lies in its interpretability and ability to identify the most influential price determinants, thereby providing useful insights for market diagnostics and feature selection in valuation modelling. Generally, however, the higher performance of the models in Mushin–Agege may be attributed to the relatively homogeneous housing structures and limited price dispersion, while the greater variability in Lekki posed challenges for all three models. This finding corroborates McGreal et al. (1998) and Raji et al. (2023), who noted that market heterogeneity often reduces model efficiency by amplifying noise in training data. It also substantiates the growing consensus in literature that no single algorithm universally outperforms others across all market contexts, and that model choice should reflect the underlying structure and complexity of the data. In line with Peterson and Flanagan (2023), this study reaffirms that ensemble models such as Random

Forest are particularly suited for urban valuation studies, where property characteristics interact in nonlinear and spatially diverse ways.

**4.6. Valuation Error-Margin**

To further assess model reliability, the study evaluated the valuation error margin generated by the three machine learning algorithms. Error-margin measures how closely the predicted property values align with actual transaction prices. Classical benchmarks include  $\pm 5\%$  to  $\pm 15\%$  (Hager and Lord, 1986), while in the Nigerian context, Ogunba and Ajayi (1998) recommend  $\pm 10\%$ . This analysis focuses exclusively on Random Forest (RF), Bayesian Ridge (BR), and LASSO Regression, respectively, examining the proportion of predictions within specific error bands across the three sub-markets, as presented in Figure 3a–c.



**Fig 3a-c: Margin of Error of selected Machine Learning Algorithms across Three Residential Sub- Markets**

Source: Field Survey, 2025

Figure 3a-c provides a comparative evaluation of the predictive performance of Random Forest, Bayesian Ridge, and LASSO regression models across the Lekki (Fig. 3a), Ikeja (Fig. 3b), and Mushin–Agege (Fig. 3c) sub-markets, using valuation error margin bands as the primary performance metric. In professional valuation practice, predictive reliability is assessed not merely by aggregate error statistics but by the proportion of estimates falling within acceptable tolerance thresholds—typically  $\pm 5\%$  to  $\pm 10\%$ —which reflect internationally recognised standards of valuation accuracy (Crosby, 2000; French, 2004; McCluskey et al., 2012).

Across all three sub-markets, Random Forest again demonstrates the strongest alignment with acceptable valuation error-margin thresholds, particularly in Lekki and Ikeja. In Lekki, a high concentration of predictions falls within the  $\pm 5\%$  and  $\pm 10\%$  bands (as shown in Fig. 3a), indicating that the algorithm effectively captures the non-linear relationships, interaction effects, and heterogeneity characteristic of premium urban housing markets. The result mirrors earlier studies on ensemble tree-based models performing better than linear and semi-parametric approaches in varied residential settings, as it accommodates complex attribute-capitalisation and spatial interactions (Antipov and Pokryshevskaya, 2012; Zurada et al., 2011; Kok et al., 2017). The strong performance observed in Ikeja further supports this alignment, as Random Forest maintains a relatively high proportion of predictions within acceptable margins despite the area’s mixed-use structure and institutional complexity. This corroborates McCluskey et al. (2013), who argue that machine-learning models perform well in heterogeneous sub-markets where sufficient structural variation enables attribute-driven price differentiation.

In Mushin–Agege, however, the predictive capacity of Random Forest weakens, with a larger share of estimates falling outside tolerance bands (See Fig. 3c). While it still outperforms Bayesian Ridge and LASSO, this decline reflects structural market constraints rather than algorithmic inadequacy. This outcome aligns with Bramley and Watkins (2015), who contend that in low-income or affordability-constrained sub-markets, price formation is weakly linked to formal property attributes and more influenced by income ceilings, informal transactions, and nonmarket adjustments. The finding, therefore, reinforces the argument that AVM accuracy is fundamentally mediated by sub-market price mechanisms.

The Bayesian Ridge regression model exhibits a more conservative predictive profile across all sub-markets. In Lekki, its predictions are more evenly distributed across valuation margin bands, with fewer estimates within the strict  $\pm 5\%$  threshold compared to Random Forest. This reflects the bias–variance trade-off inherent in Bayesian shrinkage models, which stabilise predictions but limit responsiveness to sharp price gradients and luxury premiums (Pagourtzi et al., 2003; Hoesli and MacGregor, 2000). In Ikeja, Bayesian Ridge shows increasing dispersion into wider error bands, indicating under-fitting in the presence of mixed-use complexity, consistent with findings by McCord et al. (2014). In Mushin–Agege, it marginally outperforms LASSO but still fails to achieve acceptable valuation accuracy, supporting French and Gabrielli’s (2004) remark that linear models offer limited explanatory power in socio-economically constrained markets.

The LASSO regression model records the weakest predictive capacity across all sub-markets when evaluated against professional valuation tolerance thresholds. Although some Lekki predictions fall within moderate error bands, a substantial proportion lies outside  $\pm 10\%$ , reflecting LASSO’s aggressive coefficient shrinkage. Hence, as posited by Tibshirani (1996), LASSO is primarily a variable selection tool rather than a high-precision predictive model. Its deteriorating performance in Ikeja and near-collapse in Mushin–Agege align with empirical warnings that excessive regularisation can strip away

critical market signals, leading to mean-based and professionally unacceptable estimates (Kauko and d'Amato, 2008; McCluskey et al., 2013). The study aligns with valuation literature advocating non-linear and ensemble learning approaches for automated valuation modelling and extends existing knowledge by empirically demonstrating that algorithmic superiority is sub-market contingent. It also reinforces the position advanced by French (2004) and Crosby et al. (2010) that valuation accuracy must be interpreted within each market context.

## 5. Conclusion

This paper has discussed the predictive power of three machine learning models, namely Random Forest (RF), Bayesian Ridge (BR), and LASSO Regression, to predict residential property prices in three sub-markets of Lagos Metropolis. Random Forest was the most effective model, showing the highest testing  $R^2$  values (0.74-0.90) and the lowest RMSE, MAE and MAPE scores in all sub-markets, which indicates its effectiveness in controlling nonlinear housing data and spatial heterogeneity. The Bayesian Ridge Regression model gave moderate findings when it comes to sub-markets with stable property forms, whereas LASSO Regression gave the worst results due to its sensitivity to linear assumptions and coefficient shrinkage. These findings are consistent with those of Breiman (2001) and Hong et al. (2020), who established that ensemble-based algorithms, particularly Random Forest, outperform traditional regression models in complex and heterogeneous housing markets.

The study also observed that predictive accuracy was highest in Mushin–Agege, followed by Ikeja and Lekki, indicating that simpler and more uniform markets allow for stronger model learning and generalisation. This pattern aligns with Can et al. (2019), who emphasised that algorithmic performance declines in luxury submarkets with high structural diversity and spatial heterogeneity. The findings validate the relevance of machine learning solutions and the prospects of integrating artificial intelligence into valuation practice to enhance accuracy, transparency and efficiency. For practitioners and policy-makers, the findings provide a framework within which automated valuation models (AVMs) can be developed to improve mass valuation/appraisal systems, guide investment decisions, and evidence-based planning in Nigeria's real estate sector. Further research could examine hybrid or deep learning architectures, such as gradient boosting or neural networks, including other socio-economic and spatial factors to improve the precision and scalability of the model across broader property markets.

## References

- Abidoeye, R. B. and Chan, A. P. C. (2017). Artificial neural network in property valuation: Application framework and research trends. *Property Management*, 35(5), pp. 554–571.
- Adewusi, A. O. (2024). Machine learning techniques in residential property valuation in Lagos metropolis. *Journal of African Real Estate Research*, 9(2), pp. 45–63.
- Ajayi, C. A. and Babawale, G. K. (2011). Valuation variance and reliability: A study of commercial properties in Lagos, Nigeria. *Journal of Property Research*, 28(2), pp. 121–138.
- Ajibola, M. O., Oloke, O. C. and Ogungbemi, A. O. (2022). Hedonic modelling and residential property values in Lagos metropolis. *International Journal of Housing Markets and Analysis*, 15(3), pp. 503–520.
- Aliu, I. R. (2014). Urban spatial structure and land values in Lagos. *Ethiopian Journal of Environmental Studies and Management*, 7(2), pp. 134–146.

- Alonso, W. (1964). *Location and land use: Toward a general theory of land rent*. Cambridge: Harvard University Press.
- Antipov, E. A. and Pokryshevskaya, E. B. (2012). Mass appraisal of residential apartments: An application of random forest for valuation and a CART-based approach for model diagnostics. *Expert Systems with Applications*, 39(2), pp. 1772–1778.
- Awais, A., Sakshi, R. and Shams, R. (2025). Predictive analytics for housing market trends and valuation. *Management*, 3, Article 115. <https://doi.org/10.62486/agma2025115>
- Babawale, G. K. and Ajayi, C. A. (2011). Variance in residential property valuation in Lagos, Nigeria. *International Journal of Economics and Management Sciences*, 1(6), pp. 45–54.
- Braimoh, A. K. (2007). Urban land use dynamics in Lagos, Nigeria. *Land Use Policy*, 24(2), pp. 502–515.
- Bramley, G. and Watkins, D. (2015). House-building, demographic change and affordability as outcomes of local planning decisions: Exploring interactions using a sub-regional model of housing markets in England. *Progress in Planning*, 104(2), pp. 1–35. <https://doi.org/10.1016/j.progress.2014.10.002>
- Breiman, L. (2001). Random forests. *Machine Learning*, 45(1), pp. 5–32.
- Can, A., Megbolugbe, I. and Ramaswamy, S. (2019). Statistical and machine learning approaches to housing market prediction. *Journal of Real Estate Research*, 41(4), pp. 567–590.
- Chow, C. C. and Leung, A. Y. T. (2021). Ensemble learning in housing price prediction: Evidence from Hong Kong. *Journal of Property Investment & Finance*, 39(6), pp. 589–607.
- Crosby, N. (2000). Valuation accuracy, variation and bias in the context of standards and expectations. *Journal of Property Investment & Finance*, 18(2), pp. 130–161.
- Crosby, N., Lizieri, C. and McAllister, P. (2010). Means, motive and opportunity? Disentangling client influence on performance measurement appraisals. *Journal of Property Research*, 27(2), pp. 181–201.
- Deng, L. and Zhang, X. (2025). Boosting the accuracy of property valuation with ensemble learning and explainable artificial intelligence: The case of Hong Kong. *The Annals of Regional Science*, 74(1), Article 32. <https://doi.org/10.1007/s00168-025-01365-7>
- Efron, B., Hastie, T., Johnstone, I. and Tibshirani, R. (2004). Least angle regression. *Annals of Statistics*, 32(2), pp. 407–499.
- French, N. (2004). The valuation of specialised property: A review of valuation methods. *Journal of Property Investment & Finance*, 22(6), pp. 533–541.
- French, N. and Gabrielli, L. (2004). The uncertainty of valuation. *Journal of Property Investment and Finance*, 22(6), pp. 484–500. <https://doi.org/10.1108/14635780410569470>
- Goodman, A. C. and Thibodeau, T. G. (2007). The spatial proximity of metropolitan area housing submarkets. *Real Estate Economics*, 35(2), 209–232.
- Han, H. and Hong, Y. (2023). Machine learning and housing price prediction: Evidence from Seoul. *International Journal of Housing Markets and Analysis*, 16(2), pp. 312–330.
- Harris, C. D. and Ullman, E. L. (1945). The nature of cities. *Annals of the American Academy of Political and Social Science*, 242(1), pp. 7–17.

- Hoesli, M. and MacGregor, B. D. (2000). *Property investment: Principles and practice of portfolio management*. London: Routledge. <https://doi.org/10.4324/9781315840482>
- Hong, J., Kim, H. and Lee, S. (2020). Random forest approach to housing price prediction. *Sustainability*, 12(3), pp. 1–15.
- Jimoh, R. A. (2017). Residential property market segmentation in Lagos metropolis. *Journal of African Real Estate Research*, 2(1), pp. 65–82.
- Kauko, T. and d'Amato, M. (2008). *Mass appraisal methods: An international perspective for property valuers*. New Jersey: Wiley-Blackwell.
- Kuhn, M. and Johnson, K. (2013). *Applied predictive modelling*. New York: Springer.
- MacKay, D. J. C. (1992). Bayesian interpolation. *Neural Computation*, 4(3), pp. 415–447.
- McCord, S. E., Buenenann, M., Jason, W. K. and Hadley, B. C. (2017). Integrating remotely sensed imagery and existing multiscale field data to derive rangeland indicators: Application of Bayesian Additive Regression Trees. *Rangeland Ecology & Management*, 70, pp. 644–655.
- McGreal, S., Adair, A., McBurney, D. and Patterson, D. (1998). Neural networks: the prediction of residential values. *Journal of Property Valuation and Investment*, 16(1), pp. 57–70.
- McCluskey, W. J., McCord, M., Davis, P., Haran, M. and McIlhatton, D. (2013). Prediction accuracy in mass appraisal: A comparison of modern approaches. *Journal of Property Research*, 30(4), pp. 239–265.
- Nigerian Institution of Estate Surveyors and Valuers (NIESV). (2024). Directory of registered estate surveying and valuation firms in Nigeria. Abuja, Nigeria.
- Ogunba, O. A. and Ajayi, C. A. (1998). An assessment of valuation accuracy in Nigeria. *The Estate Surveyor and Valuer*, 21(1), pp. 19–23.
- Orford, S. (2017). Housing submarkets and spatial variation in house prices in London. *Urban Studies*, 54(1), pp. 1–20.
- Oshodi, O., Ohiomah, I., Odubiyi, T., Aigbavboa, C. and Thwala, W. (2020). *Forecasting rental value of residential properties: A neural network model approach*. In: Collaboration and Integration in Construction Engineering/Management and Technology' 22 December, pp. 309–313.
- Otegbulu, A. C. (2017). Standardization of plant and equipment in a developing country: Techno-economic considerations. *Covenant Journal of Research in the Built Environment*, 6(2), pp. 88–99.
- Oyediji, J., Oshodi, O. and Oloke, O. (2018). Property rental value classification model: A case of Osogbo, Osun State, Nigeria. *Covenant Journal of Research in the Built Environment*, 6(1), pp. 52–64.
- Pagourtzi, E., Assimakopoulos, V., Hatzichristos, T. and French, N. (2003). Real estate appraisal: A review of valuation methods. *Journal of Property Investment & Finance*, 21(4), pp. 383–401.
- Park, S. and Bae, J. (2022). Housing price prediction using ensemble learning methods. *Sustainability*, 14(6), pp. 1–18.
- Peterson, S. and Flanagan, A. (2023). Automated valuation models and the future of real estate appraisal. *Journal of Property Investment & Finance*, 41(2), pp. 145–162.

- Raji, A. U., Babawale, G. K. and Adebayo, M. A. (2023). Machine learning application in Nigerian housing markets. *Journal of African Real Estate Research*, 8(1), pp. 88–104.
- Tibshirani, R. (1996). Regression shrinkage and selection via the LASSO. *Journal of the Royal Statistical Society: Series B*, 58(1), pp. 267–288.
- Tipping, M. E. and Bishop, C. M. (2007). Bayesian regression and classification. *Journal of the Royal Statistical Society: Series B*, 69(1), pp. 1–23.
- Zurada, J. M., Levitan, A. S. and Guan, J. (2011). A comparison of regression and artificial intelligence methods in property valuation. *Journal of Real Estate Research*, 33(3), pp. 349–387.

**Appendix**

**Table 2: Descriptive statistics for the Submarkets –Lekki (Lkk), Ikeja (Ikj) and Mushin-Agege (Mu-A)**

Variables	Mean			Standard Deviation			Min			25%			50%			75%			Max		
	Lkk A	Ikj	Mu- Mu-A	Lkk Mu-A	Ikj	Mu- Mu-A	Lkk Mu-A	Ikj	Mu- Mu-A	Lkk A	Ikj	Mu- A	Lkk A	Ikj	Mu- A	Lkk A	Ikj	Mu- A	Lkk Mu-A	Ikj	Mu- Mu-A
Price (N'000,000)	203. 194	221 .77	89.0 3	111. 94	118. 85	60.01	20	30	25	132 .50	146 .25	40	180	210	80	260	280	120	550	750	260
Size (sq. m)	236.82 194.95	259.82		46.6 5	58.8 9	55.78	145	145	108	193 .5	235 146. 5		240	257	185	264 .5	300	235	330	450	324
Age (years)	2.59	4.6	7.23	2.48	4.52	5.42	0	0	0	1	1	4	2	2	7	3	6	9	12	17	27
Property type	1.66	2.2 7	2.18	0.89	1.18	1.34	1	1	1	1	1	1	1	2	1	2	3	4	4	4	4
Number of bedroom	4.48	5.6 3	4.9	1.12	2.7	2.88	2	2	2	4	4	4	4	5	4	5	6	5	8	15	18
Number of bathroom	5.36	6.4 6	5.56	1.28	2.53	2.73	2	3	3	5	5	4	5	6	5	6	7	6	9	15	18
Number of toilet	4.72	5.6 4	5.03	1.17	2.69	2.88	2	2	2	4	4	4	5	5	4	5	6	5	8	15	18
Location density	2.37	2.5 8	2.31	0.51	0.57	0.52	1	1	1	2	2	2	2	3	2	3	3	3	3	3	3
Number of floors	1.21	1.1 1	1.03	0.41	0.55	0.16	1	1	1	1	1	1	1	1	1	1	1	1	2	7	2
Ceiling type	1.19	1.5 5	2.00	0.39	0.73	0.83	1	1	1	1	1	1	1	1	2	1	2	3	2	3	3

Living room size	1.15	1.06	1.18	0.36	0.23	0.56	1	1	0	1	1	1	1	1	1	1	1	1.5	2	2	2
Door type	1.58	1.87	1.59	0.91	0.85	0.5	1	1	1	1	1	1	1	2	2	3	3	2	3	3	2
Roof type	1.4	1.62	1.95	0.49	0.71	0.72	1	1	1	1	1	1	1	1	2	2	2	2	2	3	3
Availability of BQ	0.93	0.95	0.59	0.26	0.22	0.5	0	0	0	1	1	0	1	1	1	1	1	1	1	1	1
Parking space	3.99	4.56	4.59	1.14	1.2	1.07	2	2	2	4	4	4	4	4	4	4	6	6	6	6	6
Condition of facilities	2.73	2.61	2.36	0.44	0.61	0.58	2	1	1	2	2	2	3	3	2	3	3	3	3	3	3
Painting type	1.35	1.51	1.72	0.51	0.54	0.46	1	1	1	1	1	1	1	1	2	2	2	2	3	3	2

Source: Field Survey, 2025