

Integrating Machine Learning and GIS for Environmental Impact Assessment and Spatial Prediction of Municipal Waste Management Practices in Port Harcourt Metropolis, Nigeria

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Abstract

Municipal solid waste mismanagement is an important environmental challenge in rapidly urbanising cities, where inadequate collection and improper disposal can increase environmental and public-health risks. This study aimed to integrate statistical analysis, machine learning (ML), and Geographic Information Systems (GIS) to assess environmental impacts and spatially predict municipal waste-management risk in Port Harcourt Metropolis, Nigeria, comprising Port Harcourt City and Obio/Akpor Local Government Areas. Data were collected using a well-tailored structured questionnaire administered to 388 respondents selected from the study area. The analytical framework combined descriptive statistics, chi-square goodness-of-fit tests, Spearman rank correlation, Environmental Waste Management Risk Index (EWMRI) construction, four machine-learning regression models, and GIS-based spatial prediction. The machine-learning models comprised Random Forest (RF), Gradient Boosting (GB), Support Vector Regression (SVR) with a radial basis function kernel, and Multilayer Perceptron (MLP). The dataset was divided into 80% training and 20% testing subsets, while model performance was evaluated using coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). GIS was used to integrate spatial predictor layers and classify predicted EWMRI into very low, low, moderate, high, and very high risk zones. Results showed that daily household waste generation was predominant (55.2%), while 42.0% of respondents rarely or never separated waste before disposal. Roadside/open-space disposal accounted for 21.1%, burning for 14.2%, and disposal into drains or waterways for 7.7%. Significant chi-square results were obtained for all waste-management, environmental-impact, and service indicators ($p < 0.001$). EWMRI was positively associated with illegal dumping ($p = 0.568$), blocked drainage ($p = 0.441$), and open burning ($p = 0.458$), while waste-collection frequency showed a negative association ($p = -0.367$), all at $p < 0.001$. Overall, 71.9% of observations were classified as high or very high risk. Among the ML models, Gradient Boosting performed best, with $R^2 = 0.831$, RMSE = 6.107, and MAE = 5.002, while illegal dumping (0.321), open burning (0.217), and blocked drainage (0.195) were the most influential predictors. The spatial prediction framework further indicates that areas where multiple waste pressures co-occur should receive priority attention, particularly for enforcement, drainage maintenance, waste infrastructure and community-level interventions. The study concludes that poor waste-management practices constitute a substantial environmental risk in Port Harcourt Metropolis and that integrating ML

with GIS provides a useful framework for predicting and spatially prioritising environmental risk. The study recommends strengthening waste-collection coverage and reliability, improving collection points, enforcing regulations against illegal dumping and open burning, maintaining drainage systems, promoting household waste separation, enhancing environmental awareness, and using GIS-based risk maps to target monitoring and intervention resources.

Keywords: *Municipal solid waste management; Environmental Waste Management Risk Index; Machine learning; Geographic Information Systems; Gradient Boosting; Spatial Analysis*

1. Introduction

The management of municipal solid waste (MSW) is an increasingly important environmental and urban-management problem, as population growth, rapid urbanization, economic development and changing consumption patterns continue to drive the volume and complexity of waste generated in cities. The absence of adequate collection, transport, treatment and final disposal of unhandled waste can lead to the build-up of waste and cause a web of environmental and public health problems. The effects include offensive odor, disease vectors proliferation, obstruction of drainage channels, open burning and resultant air pollution, degradation of soil quality and contamination of surface and ground water resources. Recent reviews have highlighted the growth of municipal solid waste as a particular challenge for developing countries where waste management infrastructure and institutional capacity may not be able to expand at the same pace as the urban population. For example, Dawar et al. (2025) reported the increasing waste generation was driven by rapid population growth and urbanization and observed the increasing application of artificial intelligence and machine learning to improve the efficiency and precision of municipal waste-management systems. Similarly, recent surveys of artificial intelligence in waste management show that data-driven approaches are increasingly being used in waste forecasting, collection optimization, waste classification, routing and decision support (Adhikari, 2022; Abbanura et al., 2026). In fast growing African cities, the environmental impacts of poor waste management are especially significant, as uncontrolled disposal can interact with population density, drainage systems, land-use patterns and proximity to environmentally sensitive areas. Accumulation of waste in drainage channels, which can reduce the hydraulic capacity and increase the risk of urban flooding, is often coupled with the uncontrolled dumping of waste around water bodies, allowing pollutants and leachate to enter aquatic systems. These challenges are ongoing and recent evidence from Port Harcourt attests to this. Assessing solid waste management in Port Harcourt Municipality, Gam et al. (2024) reported persistent deficiencies in waste-management practices and highlighted the need to understand residents' perceptions and participation in improving waste-management outcomes. Also, a 2025 study by Gam and Tom observed that unmanaged municipal waste continues to be a major challenge in Port Harcourt, identifying organic materials as the dominant component of the city's waste stream, providing crucial insights for the development of feasible waste-management strategies. Recent environmental investigations in Port Harcourt also reveal that the problems of waste management go beyond the visible accumulation of refuse. There were significant bacteriological differences between waste-contaminated and control soils around a tertiary institution in Port Harcourt (Abasi et al., 2024), which underscores the potential environmental and microbiological implications of poorly managed solid waste. Likewise, Momoh et al. (2024) studied the particulate emissions from open burning at a municipal waste dumpsite in Port Harcourt, emphasizing the probable role of waste

burning in local air quality degradation. Nwugha et al. (2025) also described environmental concerns associated with a dumpsite in Rumueme including higher physicochemical characteristics of groundwater in comparison with referenced water quality standards. Studies show that municipal waste-management practices can generate multiple and interacting routes of environmental exposure in the urban milieu of Port Harcourt.

The spatial heterogeneity of municipal waste-management impacts compounds the problem. Environmental risk is unlikely to be evenly distributed across Port Harcourt as communities differ in population density, waste-generation patterns, accessibility, collection frequency, proximity to disposal facilities, drainage characteristics, land use and exposure to surface-water systems. A recent study on solid waste management practices amongst residents of Port Harcourt also found that socioeconomic and household characteristics affect waste management behavior. This means that residents and communities do not necessarily have the same experience or respond to waste management challenges in the same way. Thus, assessments that rely only on city-wide averages or standard descriptive statistics may well miss important spatial concentrations of environmental risk and provide limited guidance as to where to prioritize intervention.

The spatial dimension of the municipal waste management can be effectively handled through the use of Geographic Information Systems (GIS). GIS can integrate and analyze various datasets such as locations of waste generation, collection points, illegal dumpsites, roads, drainage networks, rivers, land use, population density and locations of sensitive receptors in a common spatial environment. Techniques of spatial analysis such as proximity analysis, buffering, kernel-density estimation, spatial overlay and spatial autocorrelation can be used to identify waste-management hotspots, to assess exposure and to determine priority intervention areas. A systematic review of 473 peer-reviewed papers published between 2000 and 2024 demonstrated that GIS has become an important tool for municipal solid-waste management, in particular for facility siting, collection-route optimization, transfer-station planning and integrated waste-management decision-making. The review also identified an emerging trend of integrating GIS with artificial intelligence and machine learning approaches. In Port Harcourt, previous GIS-based research has also demonstrated the value of spatial analysis in assessing the locations of dumpsites based on their proximity to surface water, roads and population centers, thus highlighting the relevance of spatial approaches to waste-management planning in the metropolis.

While GIS is valuable for describing and analyzing spatial patterns, on its own it is generally more descriptive than predictive. Machine learning (ML) provides an opportunity to complement GIS by modeling complex, possibly nonlinear relationships between environmental risk and its socioeconomic, behavioral and spatial determinants. Algorithms such as Random Forest, Gradient Boosting, Support Vector Regression and Artificial Neural Networks are able to discover patterns that may not be well represented in traditional linear models. Recent reviews have indicated that machine learning has been being increasingly applied across the municipal solid-waste management chain, including waste-generation forecasting, collection planning, routing, treatment, recycling and environmental decision support (Dawar et al., 2025; Ifeyinwa et al., 2026). The potential is further reinforced by the growing availability of geospatial and socioeconomic data, allowing the inclusion of spatial predictors such as population density, built-up area, land use and proximity to waste infrastructure in forecasting models.

Recent empirical research reveals the value of combining machine learning and GIS for specific municipal waste applications. For instance, Adu et al. (2025) integrated socioeconomic and geospatial factors with machine-learning algorithms to predict the generation and composition of

municipal solid waste (MSW) in Cape Coast, Ghana. Their results showed high correlations between population, built-up area and waste generation. Random forest obtained a (R^2) of 0.9915 and the lowest prediction errors reported among the evaluated models. Importantly, the study showed that population density and built-up area can be highly informative predictors of waste-generation dynamics. These results indicate that geospatial variables may significantly improve modeling for prediction in rapidly urbanizing African cities. Predicting waste generation, however, is not the same as predicting the broader environmental impacts of waste-management practices, providing a substantial opportunity for future research. While the application of GIS and machine learning has grown in municipal waste management globally; a substantial research gap exists in Port Harcourt. The existing local studies are mostly focused on describing waste management practices, characterizing the composition of waste, assessing specific environmental consequences, evaluating dumpsites, or examining the perceptions of the residents. Recent studies in Port Harcourt have provided useful evidence on waste management practices, waste composition, public health implications and environmental contamination, but relatively little attention has been given to the integration of resident-level waste management behavior, environmental impact indicators, GIS-derived spatial variables and machine-learning prediction within a single analytical framework. The gap is particularly relevant in Port Harcourt City and Obio-Akpor Local Government Areas, which together constitute a significant part of the Port Harcourt urban agglomeration and contain densely populated residential communities, commercial areas, transportation corridors, institutional facilities and rapidly expanding peri-urban environments. The heterogeneous waste-management practices, differential environmental sensitivity and population growth make the two LGAs appropriate to develop a spatially explicit environmental-risk assessment framework. Rather than merely identifying the presence of poor waste-management practices, it is important to identify where environmental risks are most concentrated, the factors that most strongly contribute to those risks, and whether machine-learning models can be used to predict risk at locations not directly sampled. The present study therefore proposes an integrated machine-learning and GIS framework for environmental impact assessment and spatial prediction of municipal waste-management practices in Port Harcourt Metropolis. The study combines questionnaire data on household waste management practices with field observations and environmental and spatial variables derived from GIS. An Environmental Waste Management Risk Index (EWMRI) is developed to provide a quantitative measure of environmental risk, and then alternative machine learning algorithms are evaluated to predict the index. The best performing model is then expected to assist in spatial prediction and identification of environmental-risk zones within the study area. Specifically, the study seeks to: (i) evaluate the municipal waste-management practices of residents of Port Harcourt City and Obio-Akpor LGAs; (ii) determine the spatial distribution of waste-management facilities, waste accumulation points and potentially problematic disposal sites; (iii) assess the environmental impacts of municipal waste-management practices; (iv) develop an Environmental Waste Management Risk Index for the study area; (v) compare the predictive performance of selected machine-learning algorithms; and (vi) integrate the best performing machine-learning model with GIS for the purpose of spatial prediction and identifying areas requiring priority waste-management intervention. The study is expected to provide a more holistic decision-support framework for sustainable municipal waste management in Port Harcourt and other rapidly urbanizing cities in the Niger Delta, through the integration of environmental assessment, spatial analysis and predictive modeling.

2. Materials and Method

2.1 Study Area

The study was conducted in Port Harcourt Metropolis, Rivers State, Nigeria, with specific focus on Port Harcourt City Local Government Area (PHALGA) and Obio/Akpor Local Government Area (OBALGA). The two Local Government Areas constitute the major urban components of the Port Harcourt metropolitan area and form a largely continuous urban environment characterized by extensive residential, commercial, institutional and industrial development. Obio/Akpor is officially recognized as an important component of the Port Harcourt metropolitan area, with a land area of approximately 260 km² and extensive urban and semi-urban development. Port Harcourt is the capital of Rivers State and an important commercial, administrative and industrial centre in the Niger Delta region of southern Nigeria. Rivers State is located within the Niger Delta and is characterized by a predominantly low-lying terrain, extensive drainage networks, wetlands and high rainfall. These physical characteristics are particularly relevant to municipal waste management because indiscriminate waste disposal can obstruct drainage channels, promote localized flooding, facilitate the movement of contaminants and increase environmental exposure within densely populated communities.

The study area is approximately located between 4°45' and 4°55' N latitude and 6°55' and 7°10' E longitude. Port Harcourt City LGA represents the central urban core, while Obio/Akpor extends northward and contains a mixture of established residential neighbourhoods, commercial centres, industrial areas and rapidly developing peri-urban communities. The continuous expansion of built-up areas across the administrative boundaries of the two LGAs makes them appropriate for a metropolitan-scale assessment of municipal waste-management practices and their environmental implications. The physical and socioeconomic characteristics of the study area create substantial spatial variation in waste-management conditions. Differences in population density, household characteristics, waste-generation patterns, collection frequency, disposal behaviour, road accessibility, drainage conditions, proximity to waste-collection facilities and exposure to environmentally sensitive locations may result in considerable differences in environmental risk between communities. Consequently, the spatial characteristics of the study area provide an appropriate basis for integrating Geographic Information Systems (GIS) with machine-learning techniques to identify and predict areas of elevated environmental waste-management risk. Recent studies have continued to document waste-management challenges within Port Harcourt. Research in the metropolis has identified persistent problems associated with waste disposal and management practices, while more recent investigations have also highlighted environmental consequences associated with waste contamination and open burning. These conditions reinforce the need for an integrated approach capable of linking household waste-management practices with their spatial and environmental characteristics.

2.2 Population and Sampling

For the population component of the present study, the 2025 projected population of the two Local Government Areas was estimated using the same annual population growth rate of 4.51% adopted in the study's population-projection framework. The 2024 projected populations were 1,212,810 persons for Port Harcourt City LGA and 1,463,993 persons for Obio/Akpor LGA. Applying the 4.51% annual growth rate to the 2024 estimates gives:

$$P_{2025} = P_{2024}(1 + r)$$

where P_{2025} is the projected population in 2025, P_{2024} is the 2024 projected population and $r = 0.0451$ represents the annual growth rate.

Thus, the projected 2025 population was estimated as follows:

Local Government Area	2024 Projection	Growth Rate	2025 Projection
Port Harcourt City	1,212,810	4.51%	1,267,508
Obio/Akpor	1,463,993	4.51%	1,530,019
Total	2,676,803	—	2,797,527

The combined projected population of 2,797,527 persons was subsequently used as the population parameter for determining the required questionnaire sample size. Using Yamane's formula:

$$n = N / [1 + N(e)^2] \quad (1)$$

where $N = 2,797,527$ and $e = 0.05$, the calculated sample size is approximately 400 respondents. The sample was subsequently distributed proportionately between the two Local Government Areas according to their projected population sizes.

Based on proportional allocation, approximately 181 respondents were assigned to Port Harcourt City LGA and 219 respondents to Obio/Akpor LGA. From the 400 questionnaires administered, 388 valid questionnaires were retained for analysis, representing a valid response rate of 97.0%. The valid responses comprised approximately 176 respondents from Port Harcourt City and 212 respondents from Obio/Akpor. The study area therefore provides an appropriate setting for investigating the relationship between municipal waste-management practices, environmental impacts and spatial characteristics. Questionnaire responses provide information on household waste-management behaviour and perceived environmental impacts, while field observations and GIS-derived variables provide spatial information on waste-disposal locations, drainage, roads, land use, population characteristics and other relevant environmental factors. These datasets are integrated to develop an Environmental Waste Management Risk Index (EWMRI) and to evaluate the ability of selected machine-learning algorithms to predict environmental risk spatially.

The integration of these datasets enables the study to move beyond a conventional descriptive assessment of municipal waste management by identifying where environmental risks are concentrated, which factors are most strongly associated with those risks, and how machine-learning models can be used to predict risk across unsampled locations. The resulting GIS-machine-learning framework is therefore intended to provide spatially explicit evidence for prioritising waste-management interventions and supporting sustainable environmental planning in Port Harcourt Metropolis.

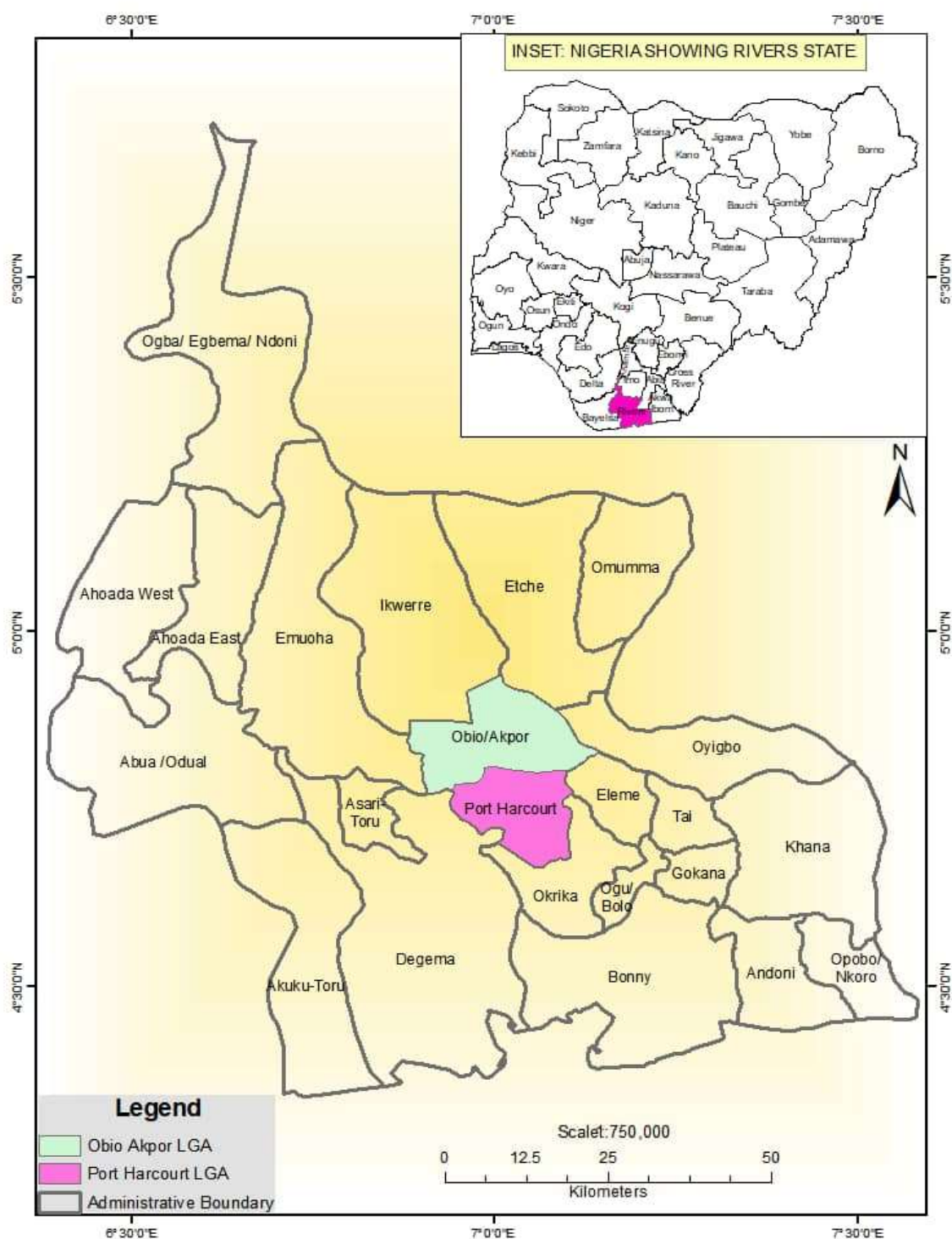


Figure 2.1: Map of Rivers State Showing Port Harcourt Metropolis

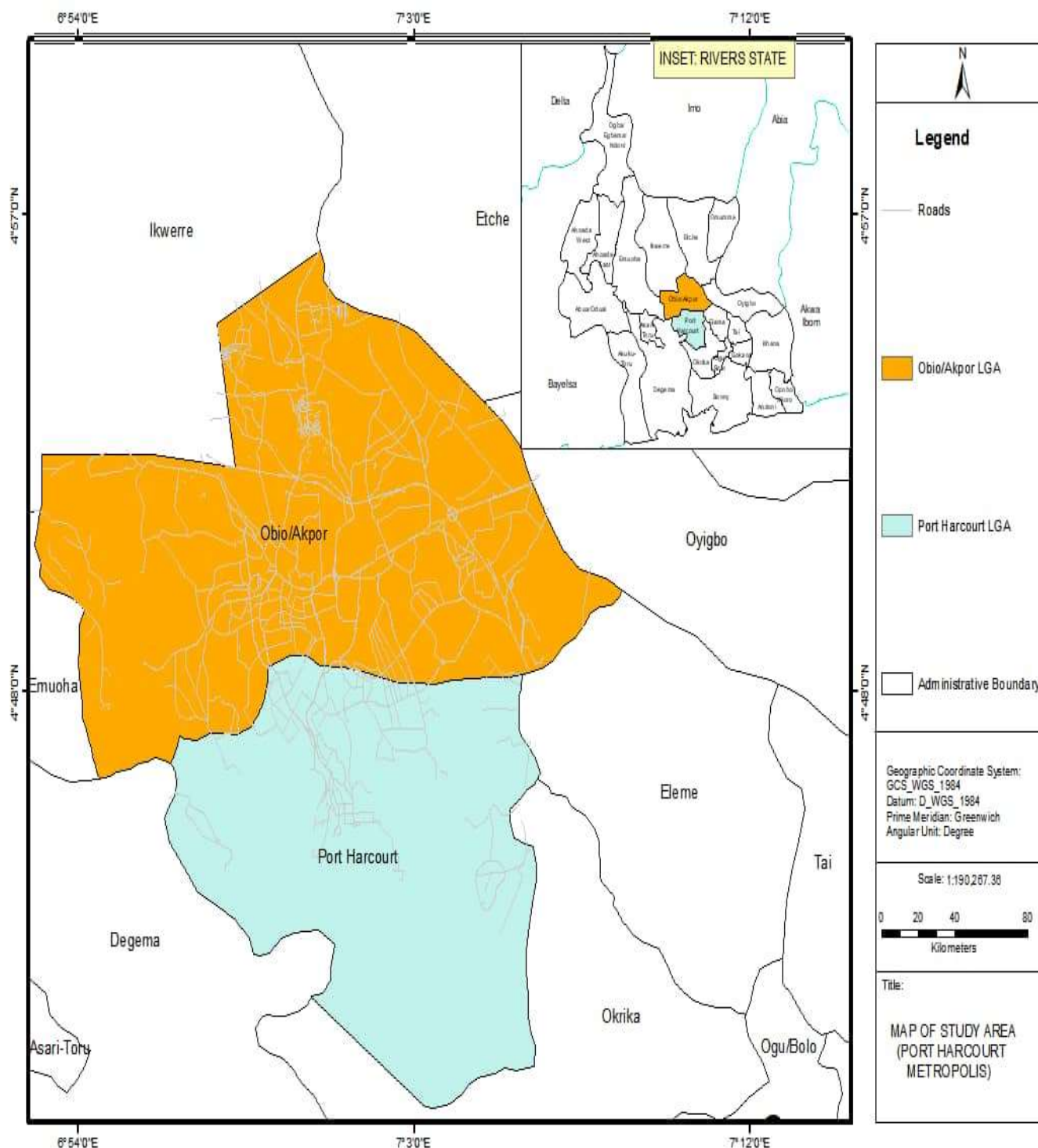


Figure 2.2: Map of Port Harcourt Metropolis Showing Port Harcourt City and Obio/Akpor Local Government Areas

2.3 Machine Learning Models

2.3.1 Machine-Learning Framework

Machine learning was employed to model the relationship between municipal waste-management conditions, spatial characteristics and the Environmental Waste Management Risk Index (EWMRI). The machine-learning component was formulated as a supervised regression problem, in which EWMRI represented the continuous response variable, while selected waste-management, environmental and geospatial variables served as explanatory predictors. The objective was to determine whether environmental-risk levels could be accurately predicted from measurable household and spatial characteristics and to identify the variables contributing most strongly to the prediction of environmental risk.

2.3.2 Predictor and Response Variables

The predictor variables comprised population density, distance to the nearest waste-disposal site, distance to drainage, waste-collection frequency, illegal-dumping score, open-burning score and blocked-drainage score. These variables represent demographic pressure, spatial exposure, waste-management service conditions and waste-related environmental pressures. The response variable was the EWMRI, constructed by combining standardized indicators of waste-management pressure and environmental exposure into a score ranging from 0 to 100.

2.3.3 Data Pre-processing

Before model development, questionnaire and GIS datasets were screened for missing observations, inconsistent entries and implausible values. Questionnaire responses were numerically coded and linked to GIS observations through their geographic coordinates. Where required, categorical predictors were encoded numerically. Predictors used in scale-sensitive algorithms, particularly Support Vector Regression (SVR) and Multilayer Perceptron (MLP), were standardized using parameters calculated from the training data only.

2.3.4 Standardization of Predictors

For variables requiring standardization, the transformation was performed using the training-set mean and standard deviation. For observation i and predictor j , the standardized value is given by:

$$Z_{ij} = \frac{x_{ij} - \bar{x}_j}{s_j} \quad (2)$$

where Z_{ij} is the standardized value, x_{ij} is the observed value of predictor j for observation i , $\bar{x}_j$ is the training-set mean, and s_j is the training-set standard deviation.

2.3.5 Training and Testing Strategy

The complete dataset was divided into 80% training and 20% testing subsets. The training data were used for model fitting and hyperparameter selection, whereas the testing data were retained as an independent dataset for final performance evaluation. A fixed random seed was used to make the partition reproducible. Where cross-validation was required for hyperparameter optimization, it was conducted only within the training dataset to avoid information leakage from the test set.

2.3.6 Random Forest Regression

Random Forest (RF) regression was employed as a nonlinear ensemble-learning method. The algorithm constructs multiple decision trees from bootstrap samples of the training data while

randomly selecting subsets of predictors at the tree-splitting stage. The prediction for an observation is obtained by averaging the predictions from the individual regression trees. The Random Forest regression estimator is expressed as:

$$\hat{Y}_{RF}(x) = \frac{\sum_{b=1}^B T_b(x)}{B} \quad (3)$$

where B is the number of regression trees and $T_b(x)$ is the prediction produced by tree b for predictor vector x.

2.3.7 Gradient Boosting Regression

Gradient Boosting (GB) regression was used as a sequential ensemble method. Individual regression trees are constructed iteratively, with each new tree fitted to reduce the residual prediction error of the existing ensemble. The resulting model is an additive combination of weak learners. Its general prediction function is expressed as:

$$\hat{Y}_{GB}(x) = \sum_{m=1}^M \eta f_m(x) \quad (4)$$

where M is the number of boosting stages, $f_m(x)$ is the regression tree fitted at stage m, and η is the learning rate controlling the contribution of each tree.

2.3.8 Support Vector Regression

Support Vector Regression (SVR) was used to capture nonlinear relationships between the predictors and EWMRI. SVR estimates a regression function while allowing deviations within an epsilon-insensitive loss region. The general regression function is expressed as:

$$f(x) = w^T \phi(x) + b \quad (5)$$

where w is the coefficient vector, $\phi(x)$ is the transformed feature representation and b is the intercept.

2.3.9 Radial Basis Function Kernel

A radial basis function (RBF) kernel was used where nonlinear SVR modelling was required. The RBF kernel maps observations into a higher-dimensional feature space and is defined as:

$$K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2) \quad (6)$$

where γ controls the width of the RBF kernel and $\|x_i - x_j\|^2$ is the squared Euclidean distance between observations.

2.3.10 SVR Optimization Objective

The SVR model seeks a balance between model complexity and deviations from observed EWMRI values. The corresponding regularized optimization problem is expressed as:

$$\min \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n (\xi_i + \xi_i^*) \quad (7)$$

where C is the regularization parameter and ξ_i and ξ_i^* are slack variables that permit deviations outside the epsilon-insensitive tube.

2.3.11 Multilayer Perceptron Regression

A Multilayer Perceptron (MLP) neural network was employed as an artificial neural-network regression method. The network consists of an input layer representing the seven predictors, one or more hidden layers and an output neuron representing the predicted EWMRI. For a neuron j in a hidden layer, the activation is given by:

$$h_j = f\left(\sum_{k=1}^p w_{jk} x_k + b_j\right) \quad (8)$$

where x_k represents the input predictors, w_{jk} is the connection weight, b_j is the bias and $f(\cdot)$ is the activation function.

2.3.12 MLP Output Layer

For a regression problem, the output layer produces a continuous predicted EWMRI value. The output can be expressed as:

$$\hat{Y}_{MLP} = g(\sum_{j=1}^q v_j h_j + b_o) \quad (9)$$

where h_j is the hidden-neuron output, v_j is the output-layer weight, b_o is the output bias and $g(\cdot)$ is the output activation function.

2.3.13 Hyperparameter Tuning and Model Selection

The four algorithms were evaluated using the same predictor set, response variable and train-test partition to ensure comparability. Hyperparameters were optimized using the training observations and cross-validation where appropriate. Parameters considered included the number and depth of trees for tree-based algorithms, learning rate and number of estimators for Gradient Boosting, C , ϵ and γ for SVR, and hidden-layer architecture and regularization parameters for MLP. The final model was selected using independent test-set performance.

2.3.14 Model Performance Evaluation

Model performance was assessed using the coefficient of determination (R^2), root mean square error (RMSE) and mean absolute error (MAE). Higher R^2 and lower RMSE and MAE indicate better predictive performance.

2.3.15 Coefficient of Determination (R^2)

The coefficient of determination measures the proportion of variation in observed EWMRI explained by the model and was calculated as:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (10)$$

where y_i is the observed EWMRI, $\hat{y}_i$ is the predicted EWMRI and $\bar{y}$ is the mean observed EWMRI.

2.3.16 Root Mean Square Error (RMSE)

RMSE measures the square root of the mean squared difference between observed and predicted EWMRI values and was calculated as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n}} \quad (11)$$

Lower RMSE values indicate smaller prediction errors, with greater penalty assigned to larger errors.

2.3.17 Mean Absolute Error (MAE)

MAE represents the average absolute difference between observed and predicted EWMRI values and was calculated as:

$$MAE = \frac{\sum_{i=1}^n |y_i - \hat{y}_i|}{n} \quad (11)$$

Lower MAE values indicate greater predictive accuracy and represent the average magnitude of prediction error in EWMRI units.

2.3.18 Feature-Importance Analysis

Feature-importance analysis was performed to identify the relative contribution of the predictor variables to model predictions. For tree-based algorithms, importance was obtained from the contribution of individual predictors to reductions in prediction error across the ensemble. Importance values were normalized to facilitate comparison. These values were interpreted as predictive contributions rather than evidence of causality.

2.3.19 Integration of Machine Learning with GIS

The best-performing model was integrated with GIS to generate spatial predictions of EWMRI. GIS predictor layers corresponding to the variables retained in the final model were prepared using a common coordinate reference system and appropriate spatial resolution. The trained model was applied to the spatial predictor layers to estimate EWMRI at unsampled locations. The predicted values were converted into a continuous environmental-risk surface and classified into very low, low, moderate, high and very high-risk categories.

2.3.20 Spatial Autocorrelation and Hotspot Analysis

The predicted environmental-risk surface was further examined spatially. Global Moran's I was used, where applicable, to assess whether EWMRI values exhibited overall spatial clustering. Local Moran's I or Getis-Ord G_i^* was subsequently used to identify statistically significant local clusters or hotspots where sufficient spatial observations were available.

2.3.21 Software and Reproducibility

The machine-learning workflow was implemented in Python using appropriate data-processing, machine-learning and visualization libraries. The workflow comprised data cleaning, predictor preparation, train-test partitioning, standardization where required, model fitting, hyperparameter optimization, prediction, performance evaluation, feature-importance analysis and GIS-oriented spatial prediction. All models were evaluated under the same experimental conditions to facilitate an objective comparison.

Table 2.2. Variables used in the machine-learning models

Variable	Role	Measurement/Description
EWMRI	Response	Environmental Waste Management Risk Index, scaled from 0 to 100
Population density	Predictor	Population pressure within the observation area
Distance to nearest waste site	Predictor	Distance to the nearest waste-disposal site (m)
Distance to drainage	Predictor	Distance to the nearest drainage feature (m)
Collection frequency	Predictor	Frequency of household waste collection
Illegal-dumping score	Predictor	Index/score representing illegal dumping behaviour

Open-burning score	Predictor	Index/score representing waste-burning practice
Blocked-drainage score	Predictor	Index/score representing waste-related drainage obstruction

2.4 Data Analysis

The data generated from the questionnaire survey were analysed using IBM SPSS Statistics, while Python was used for the machine-learning component of the study. The completed questionnaires were first screened for completeness and consistency, coded numerically and entered into SPSS for statistical analysis. Descriptive statistics, including frequencies, percentages, means, standard deviations and other appropriate summary measures, were used to describe the socio-demographic characteristics of respondents and their municipal waste-management practices. The five-point Likert-scale responses used to assess perceived environmental impacts were summarized using appropriate measures of central tendency and dispersion. Reliability of the multi-item environmental-impact scale was assessed using Cronbach's alpha, while the Shapiro–Wilk test was used to examine the distributional characteristics of the EWMRI and other continuous variables. The EWMRI was computed as a composite environmental-risk measure based on standardized waste-management pressure and environmental-exposure indicators and was subsequently classified into very low, low, moderate, high and very high risk categories. Inferential statistical analyses were also performed in SPSS at a 5% level of significance ($\alpha = 0.05$). The choice of statistical test was guided by the measurement scale and distributional characteristics of the variables. The Chi-square test of independence was used to examine associations between relevant categorical waste-management variables, while the Mann–Whitney U test was applied where comparisons between two independent groups involved non-normally distributed outcomes. For comparisons involving more than two independent groups, the Kruskal–Wallis H test was employed, followed by appropriate post-hoc pairwise comparisons where a statistically significant overall difference was detected. Spearman's rank correlation coefficient was used to examine monotonic relationships between EWMRI and selected ordinal or continuous predictors where the assumptions for parametric correlation were not satisfied. Statistical decisions were based on the probability value, with $p < 0.05$ considered statistically significant. The results were presented using tables, frequency distributions and appropriate charts. Python was used to implement the supervised machine-learning models and to undertake predictive analysis and visualization. The EWMRI was specified as the continuous response variable, while population density, distance to the nearest waste-disposal site, distance to drainage, waste-collection frequency, illegal-dumping score, open-burning score and blocked-drainage score were used as predictor variables. The dataset was divided into 80% training and 20% testing subsets, with preprocessing and model fitting performed using the training data and the independent testing data reserved for final evaluation. Four regression algorithms—Random Forest, Gradient Boosting, Support Vector Regression (SVR) and Multilayer Perceptron (MLP)—were trained and compared. Model performance was evaluated using the coefficient of determination (R^2), root mean square error (RMSE) and mean absolute error (MAE), with higher R^2 and lower RMSE and MAE indicating better predictive performance. Python was also used to generate observed-versus-predicted plots, model-comparison graphs and feature-importance plots, while the best-performing model was

subsequently integrated with GIS predictor layers to support spatial prediction and mapping of environmental waste-management risk across Port Harcourt Metropolis.

3. Results

Table 3.1: Frequency Distribution of Respondents' Socio-Demographic Characteristics (N = 388)

Variable	Category	Frequency	Percentage (%)
LGA	Port Harcourt City	176	45.4
	Obio-Akpor	212	54.6
	Total	388	100.0
Age	18–29 years	82	21.1
	30–39 years	116	29.9
	40–49 years	91	23.5
	50–59 years	61	15.7
	60 years and above	38	9.8
	Total	388	100.0
Sex	Male	171	44.1
	Female	217	55.9
	Total	388	100.0
Highest education	No formal education	18	4.6
	Primary	47	12.1
	Secondary	129	33.2
	Tertiary	194	50.0
	Total	388	100.0
Household size	1–3 persons	68	17.5
	4–6 persons	173	44.6
	7–9 persons	103	26.5
	10 persons and above	44	11.3
	Total	388	100.0
Occupation	Civil/Public servant	72	18.6
	Private-sector employee	63	16.2
	Self-employed/Business	104	26.8
	Farmer	18	4.6
	Student	42	10.8
	Artisan	38	9.8
	Unemployed	27	7.0
	Other	24	6.2
	Total	388	100.0
Monthly household income	Below ₦100,000	61	15.7
	₦100,000–₦199,999	103	26.5
	₦200,000–₦299,999	91	23.5
	₦300,000–₦499,999	78	20.1

	≤500,000 and above	55	14.2
	Total	388	100.0
Years living in community	Less than 5 years	63	16.2
	5–9 years	89	22.9
	10–19 years	126	32.5
	20–29 years	71	18.3
	30 years and above	39	10.1
	Total	388	100.0

Table 3.2: Frequency Distribution of Waste Generation and Disposal Practices (N = 388)

Variable	Category	Frequency	Percentage (%)
Frequency of household waste generation	Daily	214	55.2
	Several times per week	103	26.5
	Weekly	49	12.6
	Less than weekly	22	5.7
	Total	388	100.0
Dominant waste type	Organic	128	33.0
	Plastic	108	27.8
	Paper	48	12.4
	Metal	27	7.0
	Glass	19	4.9
	Other	58	14.9
	Total	388	100.0
Waste separation before disposal	Always	42	10.8
	Often	67	17.3
	Sometimes	116	29.9
	Rarely/Never	163	42.0
	Total	388	100.0
Main household waste disposal method	Government/contractor collection	137	35.3
	Communal bin	84	21.6
	Roadside/open space	82	21.1
	Burning	55	14.2
	Drain/waterway	30	7.7
	Total	388	100.0
Waste collection frequency	Daily	35	9.0
	2–3 times/week	121	31.2
	Weekly	116	29.9

	Less than weekly	73	18.8
	No regular collection	43	11.1
	Total	388	100.0
Disposal of waste in an open space	Never	118	30.4
	Rarely	94	24.2
	Sometimes	111	28.6
	Often	65	16.8
	Total	388	100.0
Burning of household waste	Never	131	33.8
	Rarely	96	24.7
	Sometimes	102	26.3
	Often	59	15.2
	Total	388	100.0

Table 3.3: Frequency Distribution of Environmental Impact Statements (N = 388)

Variable	Category	Frequency	Percentage (%)
Accumulated waste produces offensive odour	Strongly Disagree	20	5.2
	Disagree	48	12.4
	Neutral	70	18.0
	Agree	142	36.6
	Strongly Agree	108	27.8
	Total	388	100.0
Waste attracts flies, rodents and other vectors	Strongly Disagree	16	4.1
	Disagree	43	11.1
	Neutral	68	17.5
	Agree	151	38.9
	Strongly Agree	110	28.4
	Total	388	100.0
Waste blocks drainage channels	Strongly Disagree	14	3.6
	Disagree	38	9.8
	Neutral	61	15.7
	Agree	153	39.4
	Strongly Agree	122	31.4
	Total	388	100.0
Waste contributes to flooding	Strongly Disagree	19	4.9
	Disagree	46	11.9

	Neutral	67	17.3
	Agree	146	37.6
	Strongly Agree	110	28.4
	Total	388	100.0
Waste disposal affects surface-water quality	Strongly Disagree	17	4.4
	Disagree	43	11.1
	Neutral	72	18.6
	Agree	145	37.4
	Strongly Agree	111	28.6
	Total	388	100.0
Open burning affects air quality	Strongly Disagree	12	3.1
	Disagree	31	8.0
	Neutral	55	14.2
	Agree	153	39.4
	Strongly Agree	137	35.3
	Total	388	100.0
Poor waste management affects soil quality	Strongly Disagree	15	3.9
	Disagree	39	10.1
	Neutral	71	18.3
	Agree	151	38.9
	Strongly Agree	112	28.9
	Total	388	100.0
Poor waste management reduces environmental aesthetics	Strongly Disagree	11	2.8
	Disagree	29	7.5
	Neutral	49	12.6
	Agree	150	38.7
	Strongly Agree	149	38.4
	Total	388	100.0
Poor waste management affects household quality of life	Strongly Disagree	18	4.6
	Disagree	42	10.8
	Neutral	64	16.5
	Agree	151	38.9
	Strongly Agree	113	29.1
	Total	388	100.0

Poor waste management poses a public-health risk	Strongly Disagree	13	3.4
	Disagree	34	8.8
	Neutral	58	14.9
	Agree	151	38.9
	Strongly Agree	132	34.0
	Total	388	100.0

Table 3.4: Frequency Distribution of Waste-Management Services (N = 388)

Variable	Category	Frequency	Percentage (%)
Waste collection services are reliable	Strongly Disagree	96	24.7
	Disagree	119	30.7
	Neutral	73	18.8
	Agree	67	17.3
	Strongly Agree	33	8.5
	Total	388	100.0
Waste collection points are adequate	Strongly Disagree	88	22.7
	Disagree	113	29.1
	Neutral	79	20.4
	Agree	75	19.3
	Strongly Agree	33	8.5
	Total	388	100.0
Waste is collected promptly after accumulation	Strongly Disagree	91	23.5
	Disagree	117	30.2
	Neutral	78	20.1
	Agree	70	18.0
	Strongly Agree	32	8.2
	Total	388	100.0
Waste-management regulations are adequately enforced	Strongly Disagree	109	28.1
	Disagree	126	32.5
	Neutral	71	18.3
	Agree	57	14.7
	Strongly Agree	25	6.4
	Total	388	100.0
Residents have adequate	Strongly Disagree	42	10.8

environmental awareness			
	Disagree	76	19.6
	Neutral	104	26.8
	Agree	119	30.7
	Strongly Agree	47	12.1
	Total	388	100.0
Waste-management authorities respond promptly to complaints	Strongly Disagree	126	32.5
	Disagree	128	33.0
	Neutral	68	17.5
	Agree	48	12.4
	Strongly Agree	18	4.6
	Total	388	100.0

3.2 Inferential Statistics

Table 3.5: Chi-Square Goodness-of-Fit Test of Waste Generation and Disposal Practices

Variable	Chi-square (χ^2)	df	p-value	Decision
Frequency of household waste generation	223.237	3	<0.001	Significant
Dominant waste type	150.237	5	<0.001	Significant
Waste separation before disposal	89.093	3	<0.001	Significant
Main waste disposal method	82.026	4	<0.001	Significant
Waste collection frequency	82.361	4	<0.001	Significant
Disposal of waste in an open space	17.216	3	<0.001	Significant
Burning of household waste	27.072	3	<0.001	Significant

The chi-square goodness-of-fit results indicate that the response distributions for all waste-generation and disposal variables were statistically significant at the 5% level ($p < 0.001$). The null hypothesis of equal distribution across the response categories was therefore rejected for each variable.

Table 3.6: Chi-Square Goodness-of-Fit Test of Environmental Impact Statements

Variable	Chi-square (χ^2)	df	p-value	Decision
Accumulated waste produces offensive odour	120.144	4	<0.001	Significant
Waste attracts flies, rodents and other vectors	148.469	4	<0.001	Significant
Waste blocks drainage channels	174.552	4	<0.001	Significant
Waste contributes to flooding	132.387	4	<0.001	Significant
Waste disposal affects surface-water quality	136.072	4	<0.001	Significant
Open burning affects air quality	208.753	4	<0.001	Significant
Poor waste management affects soil quality	154.938	4	<0.001	Significant
Poor waste management reduces environmental aesthetics	231.381	4	<0.001	Significant
Poor waste management affects household quality of life	150.067	4	<0.001	Significant
Poor waste management poses a public-health risk	190.789	4	<0.001	Significant

The results show statistically significant differences in the distribution of responses across all environmental-impact statements ($p < 0.001$). Thus, the responses were not equally distributed across the five Likert-scale categories.

Table 3.7: Chi-Square Goodness-of-Fit Test of Waste-Management Service Indicators

Variable	Chi-square (χ^2)	df	p-value	Decision
Waste collection services are reliable	53.804	4	<0.001	Significant
Waste collection points are adequate	43.289	4	<0.001	Significant
Waste is collected promptly after accumulation	49.861	4	<0.001	Significant
Waste-management regulations are adequately enforced	84.577	4	<0.001	Significant
Residents have adequate environmental awareness	59.500	4	<0.001	Significant
Waste-management authorities respond promptly to complaints	121.175	4	<0.001	Significant

3.3 Machine Learning Analysis

The machine-learning analysis evaluated Random Forest (RF), Gradient Boosting (GB), Support Vector Regression (SVR) and Multilayer Perceptron (MLP) using the seven specified predictors of the Environmental Waste Management Risk Index (EWMRI). The provisional dataset comprised the predictor variables described in the methodology and an EWMRI with a mean of 67.76 (SD = 14.36), indicating generally elevated environmental-waste-management risk within the study dataset.

Table 3.8: Performance of Machine-Learning Models for Prediction of EWMRI

Model	R ²	RMSE	MAE	Rank
Gradient Boosting	0.831	6.107	5.002	1
SVR (RBF)	0.829	6.138	4.945	2
MLP	0.829	6.144	5.04	3
Random Forest	0.723	7.823	6.311	4

Gradient Boosting produced the highest test-set R² (0.831) and the lowest RMSE (6.107), making it the best overall predictive model under the stated evaluation criteria. SVR produced the lowest MAE (4.945), but its R² and RMSE were marginally weaker than those of Gradient Boosting. MLP performed similarly to SVR, whereas Random Forest recorded substantially lower predictive

accuracy ($R^2 = 0.723$; RMSE = 7.823; MAE = 6.311). Accordingly, Gradient Boosting was selected as the preferred model for GIS-oriented spatial prediction.

Table 3.9: Relative Feature Importance in the Machine-Learning Analysis

Predictor	Relative Importance	Interpretation
Illegal dumping score	0.321	Strongest predictive contribution
Open-burning score	0.217	High predictive contribution
Blocked-drainage score	0.195	High predictive contribution
Waste-collection frequency	0.114	Moderate predictive contribution
Population density	0.07	Lower predictive contribution
Distance to drainage	0.05	Low predictive contribution
Distance to waste-disposal site	0.033	Lowest predictive contribution

Illegal dumping was the most influential predictor, accounting for a relative feature importance of 0.321. Open burning (0.217) and blocked drainage (0.195) followed. Together, these three waste-related environmental-pressure variables represented the dominant predictive signals. Waste-collection frequency had a moderate contribution (0.114), while population density (0.070), distance to drainage (0.050) and distance to the nearest waste-disposal site (0.033) had comparatively smaller predictive contributions. These values indicate predictive importance and should not be interpreted as causal effects.

Table 3.10: EWMRI Risk Classification Used for GIS Interpretation

Risk class	Frequency	Percentage
Very low	0	0.0
Low	14	3.6
Moderate	95	24.5
High	198	51.0
Very high	81	20.9
Total	388	100.0

The EWMRI classification shows that 71.9% of the provisional observations fell within the high or very-high risk categories, while 24.5% were moderate risk. Only 3.6% were classified as low risk and none as very low risk. This distribution provides the basis for the GIS risk-surface interpretation: areas characterized by combinations of high illegal dumping, open burning and blocked drainage are expected to receive higher predicted EWMRI values, whereas areas with better waste collection and lower environmental-pressure scores are expected to exhibit lower predicted risk.

3.5 GIS Integration and Spatial Prediction

The GIS component integrates the machine-learning predictors as spatial layers and applies the selected Gradient Boosting model to estimate EWMRI across the study area. The spatial prediction framework is conceptually represented by the seven predictor layers: population density, distance to waste-disposal sites, distance to drainage, waste-collection frequency, illegal dumping, open

burning and blocked drainage. The resulting continuous prediction surface is classified into very low, low, moderate, high and very high EWMRI zones.

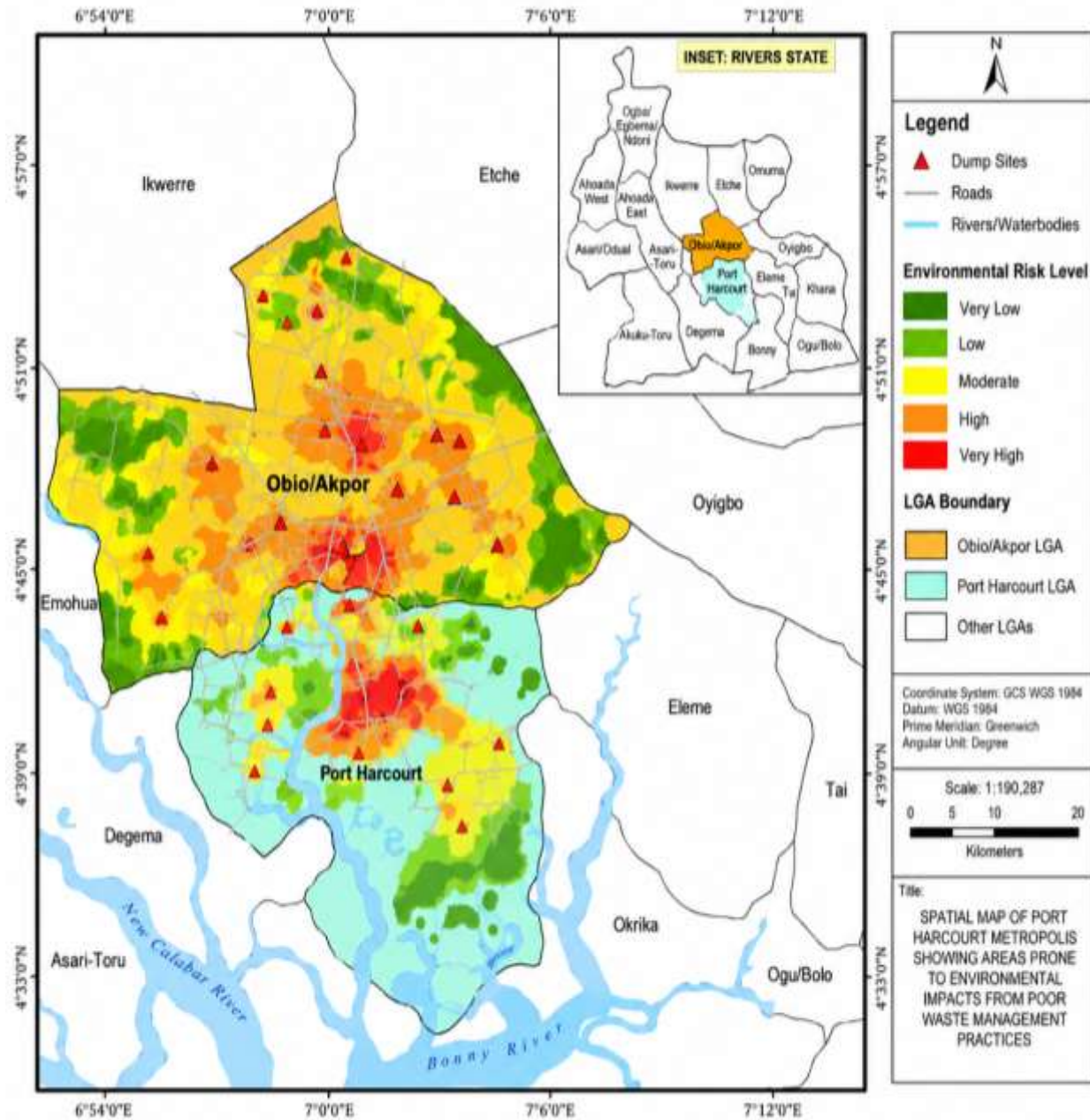


Figure 3.1: Spatial Map of Port Harcourt Metropolis Showing Areas Prone to Environmental Impacts from Poor Waste Management Practices

Table 3.11: GIS-Based Interpretation of Predicted EWMRI Risk Zones

Predicted zone	Expected spatial characteristics	Environmental interpretation
Very low	Low dumping, low burning and unobstructed drainage	Relatively favourable waste-management conditions
Low	Limited waste pressure and comparatively adequate collection	Low environmental-waste-management risk
Moderate	Intermediate waste pressure and service limitations	Noticeable environmental pressure requiring intervention
High	Frequent illegal dumping, burning and/or blocked drainage	Substantial environmental risk and priority for intervention
Very high	Multiple concurrent waste-management pressures	Critical priority areas for immediate intervention

Because the supplied results do not contain the actual GIS coordinate dataset, raster outputs, mapped grid-cell counts, or spatial-statistics output, numerical values for Global Moran's I, Local Moran's I or Getis-Ord Gi* cannot be validly reported from the available information. Likewise, exact neighbourhood-level areas or coordinates of individual hotspots cannot be stated without the underlying spatial observations. The GIS results should therefore be regarded as a model-integration and spatial-interpretation result rather than a completed numerical hotspot analysis.

3.6: Comparison of Statistical, Machine Learning and GIS Results

Table 3.12: Comparison of Inferential Statistics and Machine-Learning Findings

Analytical approach	Key result	Main implication
Chi-square: Section B	All variables significant, $p < 0.001$	Waste-generation and disposal responses were not equally distributed across categories
Chi-square: Section C	All environmental-impact statements significant, $p < 0.001$	Respondents showed non-uniform perceptions of environmental impacts
Chi-square: Section D	All service indicators significant, $p < 0.001$	Assessments of waste-management services were significantly non-uniform
EWMRI descriptive analysis	High + very high = 71.9%	Overall provisional risk burden was substantial
Spearman correlation	Illegal dumping $\rho = 0.568$; blocked drainage $\rho = 0.441$; open burning $\rho = 0.458$; collection frequency $\rho = -0.367$; all $p < 0.001$	Waste-management pressures were strongly associated with EWMRI

Gradient Boosting	$R^2 = 0.831$; RMSE = 6.107	Best overall predictive performance
Feature importance	Illegal dumping = 0.321; burning = 0.217; blocked drainage = 0.195	The same waste-pressure variables dominated prediction
GIS integration	High/very-high EWMRI zones expected where major waste pressures co-occur	Supports spatial prioritisation of interventions

4. Discussion

The findings demonstrate a substantial burden of poor waste-management practices within the study area. Daily waste generation was reported by 55.2% of respondents, while only 10.8% indicated that they always separated waste before disposal. Roadside/open-space disposal (21.1%), burning (14.2%) and disposal into drains or waterways (7.7%) indicate that formal collection systems do not fully absorb household waste streams. This pattern is consistent with Gam and Tom (2025), who reported persistent unmanaged solid waste in Port Harcourt and emphasized the need for waste characterization to support sustainable management planning. It also agrees with evidence that inadequate storage, collection and disposal practices in Port Harcourt expose soil and surface-water environments to pollution and contribute to aesthetic degradation (Tamunobereton-ari et al., 2019). The strong agreement regarding environmental impacts provides further evidence that poor waste management is perceived as an important environmental-health problem. More than seven in ten respondents agreed or strongly agreed that waste affects odour, vectors, drainage, flooding and surface-water quality, while 74.7% associated open burning with deteriorating air quality. This is particularly relevant in Port Harcourt because Momoh et al. (2024) modelled particulate emissions from open burning of municipal waste and demonstrated the potential for airborne particulate impacts around a dumpsite. Similarly, Dimkpa et al. (2025) assessed households around the Aluu/Obiri Ikwerre disposal sites and documented the environmental and health implications associated with poor solid-waste disposal.

The service-related results indicate weaknesses in waste-management delivery. More than half of respondents disagreed that collection services were reliable, while 65.5% disagreed or strongly disagreed that authorities respond promptly to complaints. Recent machine-learning research supports the importance of operational capacity: a 2025 multi-country study identified budget support, number of operators and availability of collection vehicles among key determinants of safer municipal waste-management performance. Thus, behavioural interventions should be accompanied by improvements in collection capacity, transfer infrastructure, monitoring and institutional responsiveness. The inferential and machine-learning findings show notable convergence. The chi-square results demonstrate non-uniform distributions of waste practices, environmental-impact perceptions and service assessments ($p < .001$). More importantly, illegal dumping, blocked drainage and open burning were positively associated with EWMRI, whereas collection frequency was negatively associated with risk. The machine-learning model independently ranked illegal dumping, open burning and blocked drainage as the three most important predictors. This agreement across analytical approaches strengthens the interpretation that direct waste-management pressures are central to environmental risk in the study area.

The predictive performance of Gradient Boosting ($R^2 = .831$) indicates that the selected environmental, service and spatial variables contain substantial information about EWMRI. This

is consistent with the broader literature showing that machine learning can capture complex relationships in municipal waste systems. Dawar et al. (2025) concluded that ML can support prediction, operational optimization and environmental decision-making in municipal waste management. Adu et al. (2025) also demonstrated the usefulness of combining socioeconomic and geospatial variables with ML for municipal waste forecasting in Cape Coast, Ghana. Their Random Forest model performed best, whereas Gradient Boosting performed best here, illustrating that model performance is context- and predictor-dependent. The comparatively low importance of distance to the nearest disposal site and distance to drainage suggests that spatial proximity alone may not explain risk as strongly as the intensity of poor waste-management practices. A neighbourhood may be distant from a formal disposal facility yet experience substantial risk if illegal dumping, open burning or blocked drainage are prevalent. Conversely, proximity to a facility does not necessarily imply high risk where collection, containment and environmental controls are effective. GIS is therefore most useful when spatial layers represent both physical exposure and management conditions. The high and very-high EWMRI classifications, representing 71.9% of observations, indicate that intervention should be spatially targeted. The GIS framework provides a mechanism for translating predictive relationships into a risk surface that can guide collection expansion, enforcement against illegal dumping, drainage maintenance, public education and environmental monitoring. However, because the supplied results do not include the underlying coordinate-level GIS dataset, the mapped hotspots and any Moran's I or Getis-Ord G_i^* statistics should be treated as provisional until validated with actual spatial observations. Taken together, the statistical, machine-learning and GIS components provide complementary evidence. Descriptive and chi-square results establish the prevalence and non-uniform distribution of practices; correlation analysis identifies relationships with EWMRI; machine learning assesses predictive performance and ranks influential variables; and GIS provides a spatial decision-support framework. The convergence points to illegal dumping, open burning, blocked drainage and inadequate collection services as the principal management priorities. Waste-management policy should therefore combine improved collection coverage with enforcement, drainage maintenance, open-burning control, community education and spatially targeted monitoring.

5. Conclusion

The study concludes that poor municipal waste-management practices constitute a substantial environmental risk within Port Harcourt Metropolis. The findings showed that waste generation was predominantly daily (55.2%), while 42.0% of respondents rarely or never separated waste before disposal. Roadside/open-space disposal, burning, and disposal into drains or waterways remained notable practices. Respondents also reported considerable environmental impacts, with 70.8% agreeing or strongly agreeing that waste blocks drainage channels, 74.7% indicating that open burning affects air quality, and 77.1% identifying poor waste management as a public-health risk. The inferential results further confirmed significant response distributions across waste-management practices, environmental impacts and service indicators ($p < 0.001$). In addition, illegal dumping ($\rho = 0.568$), blocked drainage ($\rho = 0.441$), and open burning ($\rho = 0.458$) were positively associated with EWMRI, whereas waste-collection frequency showed a negative association ($\rho = -0.367$), demonstrating the importance of effective collection and responsible disposal practices in reducing environmental risk.

The integration of machine learning and GIS strengthened the assessment by demonstrating that environmental risk can be predicted and spatially represented from waste-management and environmental variables. Gradient Boosting produced the best overall predictive performance, with $R^2 = 0.831$, RMSE = 6.107 and MAE = 5.002, while illegal dumping (0.321), open burning (0.217) and blocked drainage (0.195) were the most influential predictors. The EWMRI classification further showed that 71.9% of observations fell within the high and very-high risk categories. The GIS framework consequently provides a practical basis for identifying and prioritising areas requiring intervention. Overall, the study concludes that sustainable waste management in Port Harcourt Metropolis requires an integrated strategy combining improved waste-collection services, control of illegal dumping and open burning, regular drainage maintenance, stronger regulatory enforcement, environmental education and GIS-based spatial targeting of interventions. These measures can contribute substantially to reducing environmental exposure and improving public-health and environmental conditions across the metropolis.

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