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DEVELOPMENT OF ROAD REHABILITATION MODEL IN FLOOD-PRONE AREAS: A CASE STUDY OF REEVES STREET LEKKI, LAGOS

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Abstract

This study presents a novel predictive framework for road rehabilitation in flood-prone urban environments. The research integrates precipitation analysis, geotechnical investigation, and probabilistic modeling to develop a comprehensive road deterioration prediction system. The precipitation data analysis from 2014-2024 revealed extreme rainfall events up to 198.5 mm daily. Geotechnical testing showed that the coefficients of uniformity (Cu) of the subgrade ranged from 5.05 to 6.11, while coefficients of curvature (Cc) varied between 2.10 and 2.66, field moisture content varied between 5.29% to 10.32%, maximum dry density values ranged from 671.80 kg/m³ to 715.14 kg/m³, with corresponding optimum moisture content values between 7.07% and 8.65%. the California Bearing Ratio (CBR) exceeding 10% across all test locations, though falling short of the 30% requirement for sub-base applications using FMWH (2013) guidelines. Community surveys of 120 residents revealed that 58% rated post-flood road conditions as "poor," with 91% experiencing vehicle or property damage. A dual-model approach combining Storm Drain analysis and Markov Chain simulation was developed to predict pavement deterioration. The Markov model demonstrated that under normal conditions, roads deteriorate from 100% "Good" condition to 19.69% over 10 years, while high precipitation scenarios accelerate this to just 2.82% remaining in "Good" condition.

Keywords

Road rehabilitation, flood-prone areas, Markov chain, urban infrastructure, predictive modeling

1. INTRODUCTION

Urban flooding represents one of the most significant challenges facing rapidly developing cities in sub- Saharan Africa, with road infrastructure bearing the brunt of climate-induced deterioration (Adegun, 2023). Lagos State, Nigeria's economic hub, exemplifies this challenge, with its low-lying coastal geography making it particularly vulnerable to flood-related infrastructure damage. The combination of intensive rainfall, inadequate drainage systems, and rapid urbanization creates a complex web of factors that accelerate road deterioration beyond conventional maintenance capabilities. Lagos State's vulnerability to flooding has been well-documented since the first recorded event in 1947 (Bates and De Roo, 2000). The frequency of flood events has increased significantly over recent decades, with major events recorded in 1968, 1969, 1970, 1971, 1972, 1974, 1999, 2000, and 2004 (Adelekan, 2011). This increasing trend reflects the complex interaction between climatic changes and anthropogenic factors.

The Lagos metropolitan area continues to experience population growth and spatial expansion, negatively impacting the physical environment, particularly drainage systems (Nkeki et al,, 2013). As more people settle in flood-prone areas and obstruct natural drainage channels, the potential for flood damage increases exponentially (Obiefuna et al., 2021). The relationship between waste management and flooding cannot be overlooked, as inadequate waste collection and disposal practices contribute to drainage system blockages (Onifade et al., 2023).

Traditional reactive maintenance approaches have proven inadequate for addressing the scale and complexity of flood-induced road deterioration (BITRE, 2004). Flood risk and road rehabilitation quality in Lagos have been studied using different methods. Many researchers have used cross-sectional studies with questionnaires and secondary data to understand community experiences and infrastructure problems. Particularly, Mayowa and Afolashade (2017) examined 84 residents in Ikeja, Lagos to see how road rehabilitation affected property values using descriptive statistics like weighted mean, frequency, and percentage distribution. The results showed that time lost from road diversions became much less of a problem after the rehabilitation work was done. Geospatial technologies have improved how researchers assess flood impacts. Adelekan (2016), Nkwunonwo *et al.* (2016) and Obiefuna *et al.* (2021) used satellite images, elevation data, remote sensing, and GIS methods along with numerical hydrodynamic modeling to study flood effects on communities. Ademola *et al.* (2021) did a vulnerability assessment of the Eti-Osa area in Lagos using GIS and remote sensing to process and analyze spatial data. They found five flood vulnerability zones: very highly vulnerable (23.59%), highly vulnerable (12.23%), moderately vulnerable (10.04%), less vulnerable (9.52%), and non-vulnerable (44.62%) zones.

Urban flood modeling has mostly used hydraulic and hydrologic (H&H) methods. One-dimensional models like HEC-RAS and two-dimensional models like the urban inundation model are popular because they work well for simulating flood inundations using shallow water equations (Chen et al., 2007; Chaudhry et al., 2018). However, these models require a lot of computing power and are hard to use for entire cities. To solve these problems, researchers have created simpler H&H models, including cellular automata (CA)-based and topographic depression-based methods (Jamali et al., 2019). CA models still need a lot of resources though (Liu et al., 2015). For road applications, H&H models are often used to estimate flood exposure. Coles *et al.* (2017) used FloodMap to check emergency access in York, UK while Versini (2012) tried to validate results by connecting past road flood data with water simulations for real-time flood alerts. These models are useful, but they mainly show road exposure from past floods instead of predicting ongoing flood risks for roads (Smith et al., 2012; Lyu et al., 2019; Hou et al., 2021).

Machine learning has changed how researchers predict floods and manage infrastructure. Abu-Salih *et al.* (2023) created a road network flood risk detection model using optimized ensemble learning for the Great Southern Region of Western Australia. With over 3 million observations, they tested different machine learning models like ensemble-based, generic, and AutoML classifiers. The optimized ensemble Extremely Randomized Trees (ExtraTrees) classifier worked best with an average ROC AUC value of 90%, beating other top classifiers and known AutoML tools. Yuan *et al*. (2023) also predicted road flooding risks using topographic, hydrologic, and temporal precipitation features with machine learning models. They found that precipitation was the most important factor for predicting road flood risk, and topographic features mattered more than hydrologic features. Kenley *et al.* (2014) proposed a location-based framework providing an underlying concept for effective efforts in linking predictive and reactive maintenance activities. This framework aimed to optimize and prioritize road maintenance and rehabilitation work in flood-susceptible areas, based on case studies designed to minimize life-cycle costs of major rain and flood events.

Current road rehabilitation practices in Nigeria rely heavily on post-failure interventions, leading to higher costs and extended periods of service disruption (Kenley et al., 2024). The absence of systematic approaches that integrate environmental factors, soil conditions, and community experiences into planning processes has perpetuated a cycle of inadequate infrastructure resilience.

This study aims to develop a comprehensive predictive framework for road rehabilitation in flood-prone areas by analyzing precipitation patterns and their correlation with infrastructure deterioration, conducting comprehensive geotechnical assessment of subgrade conditions, integrating community experiences and perceptions of flood-related road damage, developing a probabilistic model for predicting pavement condition transitions, and creating a practical framework for proactive infrastructure maintenance planning.

2. MATERIALS AND METHOD

2.1 Study Area Description

Figure 1: Field Photograph Depicting Flooding Conditions at Lekki [Source: Researcher]

Lekki is located in Lagos State, Nigeria, between latitudes 6°23'N and 6°41'N and longitudes 2°42'E and 3°42'E. The area is characterized by low-lying coastal topography with approximately 78% wetlands and 22% lagoons and creeks as shown in Figure 1.

2.2 Precipitation Data Analysis

Historical precipitation data spanning 2014-2024 was obtained from the Nigerian Meteorological Agency (NiMet). The analysis focused on descriptive statistics including mean, standard deviation, variance, skewness, and kurtosis to characterize rainfall patterns and identify extreme events.

2.3 Geotechnical Investigation

Soil samples were collected at four chainages (0 m, 100 m, 200 m, 300 m) along Reeve Street, Lekki, at minimum depths of 1 m as shown in figure 2a. Laboratory testing included sieve analysis for particle size distribution, natural moisture content determination, standard Proctor compaction tests, California Bearing Ratio (CBR) test, and compressive strength test of paving stones as shown in figure 2b and 2c. All tests were conducted according to BS 1377-4:1990 standards (Echandu, 2020).

2.4 Community Survey

A structured questionnaire was administered to 120 residents along Admiralty Way, Lekki Phase 1. The survey captured experiences with flood frequency, road conditions, vehicle damage, and rehabilitation preferences using stratified random sampling method.

2.5 Base Model

A performance prediction model was developed integrating multiple parameters as shown in equation 1:

$$P_r = \propto \ + \beta_1 (\mathrm{Sg}') + \beta_2 (\mathrm{D_e}) + \beta_3 (\mathrm{C_s}) + \beta_4 (\mathrm{M_c}) + \varepsilon$$

$$P_r = \propto \ + \beta_1 (\mathrm{Sg}') + \beta_2 (\mathrm{D_e}) + \beta_3 (\mathrm{C_s}) + \beta_4 (\mathrm{M_c}) + \varepsilon \quad (1)$$

Where: P_r = Predicted road performance,
Sg' = Adjusted subgrade strength,
D_e = Drainage effectiveness,
C_s = Compressive strength,
M_c = Moisture content,
α, β = Model coefficients, and
ε = Error term. Philip and Al-Jassmi (2024)

2.6 Markov Chain Model

A three-state Markov chain was developed with states representing Good Condition (G), Moderate Condition (M), and Poor Condition (P). Transition probability matrices were developed for normal and high precipitation scenarios based on observed deterioration patterns and environmental factors. The transition probability matrix is expressed as in equation 2:

$$P = \begin{bmatrix} P_{GG} & P_{GM} & P_{GP} \\ P_{MG} & P_{MM} & P_{MP} \\ P_{PG} & P_{PM} & P_{PP} \end{bmatrix} \begin{bmatrix} P_{GG} & P_{GM} & P_{GP} \\ P_{MG} & P_{MM} & P_{MP} \\ P_{PG} & P_{PM} & P_{PP} \end{bmatrix} \quad (2)$$

3. RESULTS AND DISCUSSION

Table 1 revealed significant temporal variability in rainfall patterns across the study period. Mean daily rainfall ranged from 3.85 mm/day in 2015 to 6.26 mm/day in 2023, with the latter representing the highest average in the dataset. Maximum daily rainfall values showed extreme variations, from 99.8 mm in 2018 to a peak of 198.5 mm in 2021.

All years exhibited positive skewness ranging from 3.65 to 6.69, indicating that the majority of days experienced low to moderate rainfall punctuated by extreme events. Kurtosis values were exceptionally high in 2021 (66.68) and 2022 (56.34), indicating the concentration of extreme rainfall events in relatively few days.

Table 1: Descriptive Statistics of the precipitation data in Lekki

Year	Maximum	Mean	Std. Deviation	Variance	Skewness	Kurtosis
Y2014	120.60	6.18	16.12	259.82	4.08	20.18
Y2015	113.00	3.85	11.13	123.88	4.82	32.25
Y2016	112.50	4.09	12.24	149.94	5.41	36.92
Y2017	176.50	6.12	16.95	287.34	4.92	34.72
Y2018	99.80	4.72	13.33	177.74	3.91	17.14
Y2019	116.60	5.96	15.21	231.27	3.65	15.66
Y2020	164.70	4.96	17.44	304.12	6.14	45.69
Y2021	198.50	5.01	15.69	246.30	6.69	66.68
Y2022	169.00	4.74	16.47	271.20	6.69	56.34
Y2023	179.70	6.26	16.26	264.35	5.27	41.38
Y2024	139.10	4.46	14.12	199.45	4.97	31.74

Note that the minimum of all year is 0 (zero) and due to the minmum the variance is equal to maximum

Source: Researcher IBM SPSS STATISTICS 2023

3.1 Particle Size Distribution

Table 2 revealed well-graded sandy soils across all test locations. The percentage of sand particles ranged from 74.24% to 77.34%, with gravel content between 16.88% and 24.88%. Fine content remained below 8% at all locations, indicating good drainage characteristics. The Federal Ministry of Works and Housing (2013) stated that the fine content for sub-grade, sub-base, and base materials should not exceed 35%.

The coefficients of uniformity (Cu) ranged from 5.05 to 6.11, all exceeding the threshold of 4 for well-graded soils. Coefficients of curvature (Cc) varied between 2.10 and 2.66, indicating suitable gradation for construction applications.

Table 2: Result of the Sieve Analysis

Parameter	CH 00m	CH 100m	CH 200m	CH 300m
% Gravel	17.31	23.89	16.88	24.88
% Sand	75.31	75.3	77.34	74.24
% Fines	7.38	0.81	5.78	0.88

Cu (Uniformity Coeff.)	5.93	5.805	5.052	6.107
Cc (Coefficient of Curvature)	2.1	2.661	2.344	2.536

3.2 Moisture Content and Compaction

Table 3 showed that the moisture content and maximum dry density varied significantly across chainages, ranging from 5.29% at CH 200 m to 10.32% at CH 300 m. Maximum dry density values ranged from 671.80 kg/m³ to 715.14 kg/m³, with corresponding optimum moisture content values between 7.07% and 8.65%.

Table 3: Summary of the Field Moisture Content, OMC and MDD

Chainage	Average Moisture Content (%)	OMC (%)	MDD (kg/m3)
CH 0m	8.28	7.07	702.19
CH 100m	6.02	8.39	671.8
CH 200m	5.29	8.65	715.14
CH 300m	10.32	7.73	686.24

3.3 California Bearing Ratio

Table 4 showed that the CBR values at 2.5 mm penetration ranged from 11.02% to 14.01%, all exceeding the minimum 10% requirement for subgrade applications according to FMWH specifications (Philip and AlJassmi, 2024). However, none of the test locations achieved the 30% minimum required for sub-base materials.

Table 4: Summary of CBR at 2.5 and 5.0 at all chainage

CBR Values	CH 00m	CH 100m	CH 200m	CH 300m
CBR at 2.5 (%)	14.01	11.31	11.61	11.02
CBR at 5.0 (%)	18.29	14.05	15.71	15.22

3.4 Community Survey Results

Figure 3 showed that from that 72% of respondents experience flooding frequently and very frequently, with only 5% reporting rare occurrences. Regarding causes, 32% attributed flooding to a combination of heavy rainfall, poor drainage systems, and rising sea levels. Post-flood road conditions were rated as "poor" and "very poor" by 80% of respondents.

An overwhelming 91% of respondents reported experiencing vehicle or property damage due to flood- damaged roads. The most common challenges included increased travel time (39%), inaccessibility (19%), and vehicle damage (14%). Drainage systems were a critical concern, with 78% of respondents stating they were ineffective in managing floodwater. Additionally, 93% confirmed that floods had damaged drainage channels in their locality.

3.5 Compressive Strength of Paving Stones

The manufactured paving stones demonstrated progressive strength gain over the curing period. Table 5 showed that the compressive strength increased from 35 N/mm² at 7 days to 59.95 N/mm² at 28 days, significantly exceeding the 30 N/mm² minimum requirement specified in BS EN 1338 (Federal Ministry of Works and Housing, 2013)

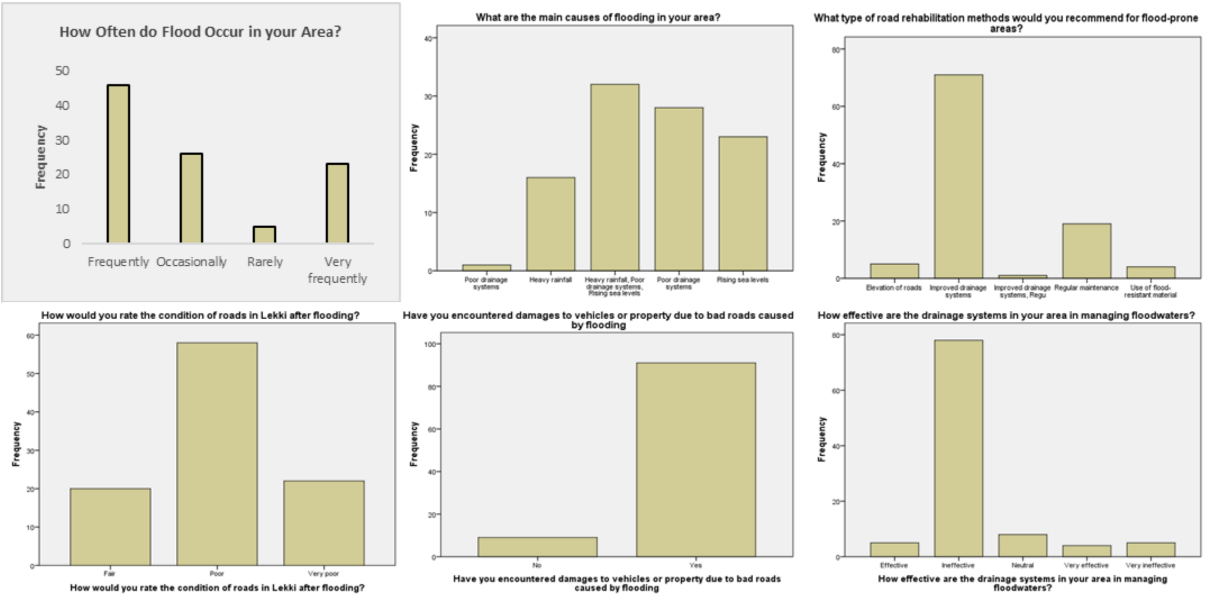

Figure 3: The response of the community on the impact of flood in Lekki [Source: Researcher]

Table 5: Summary of the Compressive Strength of Paving Stones

S/N	Days	Test 1	Test 2	Average
1	7 days	36	34	35
2	14 days	40.2	39.4	39.8
3	21 days	51	49	50
4	28 days	58.7	61.2	59.95

3.6 Base Model Results

The Storm Drain-based performance model predicted varying performance levels across the test chainages. Table 6 showed that CH 0 m, CH 100 m, and CH 200 m received ratings from "Good" to "Excellent," while CH 300 m was classified as "Failure" requiring minor improvements.

Table 6: Summary of the basic model for the road performance prediction

Chainage	Adjusted Subgrade Strength (Sg′)	Drainage Effectiveness (De)	Predicted Performance (Pr)	Status
CH 00m	15.16%	0.00007	1.364	Good performance.
CH 100m	18.02%	0.00007	2.508	Excellent performance.
CH 200m	21.79%	0.00007	4.016	Excellent performance.
CH 300m	10.14%	0.00007	-0.644	Failure; minor improvements needed.

3.7 Markov Chain Simulation

The Markov chain model provided insights into long-term pavement deterioration under different scenarios which was visually presented in Figure 4 and key insight are summarized below:

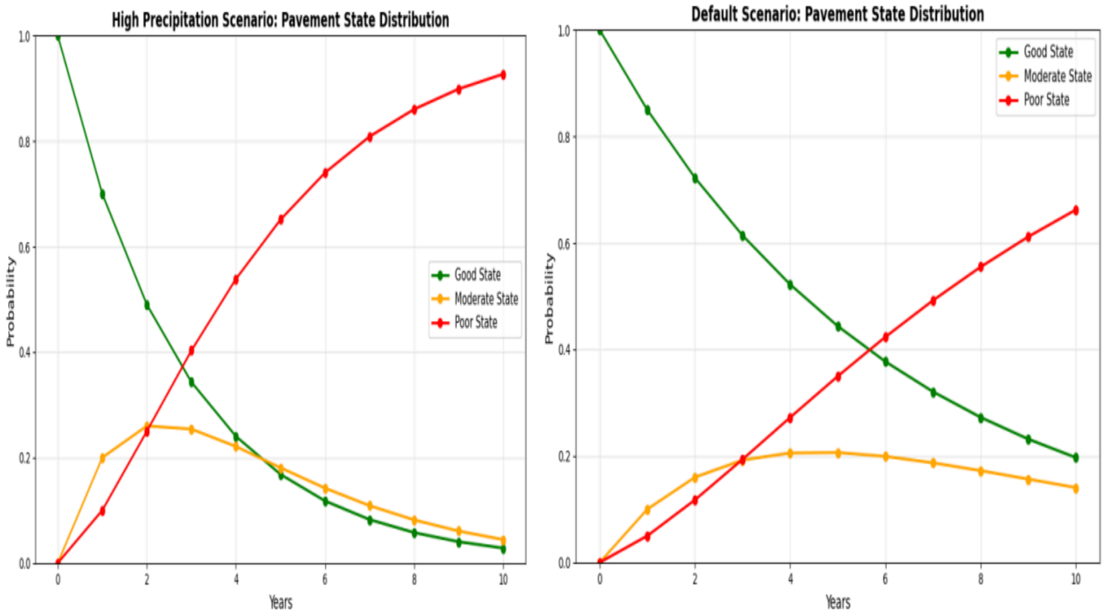

Figure 4: The Result of the Markov Chain in Default and High Precipitation Scenario

Default Scenario

i. Year 0: *Good: 100%*

ii. Year 5: *Good, 20.64% Moderate, 34.99% Poor: 44.37%*

iii. Year 10: *Good: 19.69%, Moderate: 14.06%, Poor: 66.26%*

High Precipitation

i. Year 0 - Good*:* 100%

ii. Year 5 - *Good:* 16.81%, *Moderate:* 18.06%, *Poor:* 65.13%

iii. Year 10 - *Good:* 2.82%, *Moderate:* 4.44%, *Poor:* 92.73%

The dramatic difference between scenarios highlights the accelerating effect of excessive precipitation on pavement deterioration.

3.7 Model Validation and Reliability

The developed framework demonstrated strong correlation between predicted and observed conditions. The base model successfully identified CH 300m as the most vulnerable section, which aligned with both geotechnical test results and community observations of poor road conditions in that area.

Statistical validation through SPSS analysis confirmed the reliability of the precipitation data trends and their relationship to infrastructure deterioration patterns. The integration of multiple data sources (technical, meteorological, and community-based) strengthened the model's predictive capability and real-world applicability.

4. CONCLUSION

This study successfully developed and validated a comprehensive predictive framework for road rehabilitation in flood-prone urban areas using Lekki, Lagos as a case study. The research demonstrates that systematic integration of meteorological, geotechnical, and community data can provide reliable tools for infrastructure planning and management.

Key findings include extreme rainfall events up to 198.5 mm daily with highly skewed distributions, well-graded sandy soils with adequate drainage properties but variable compaction and bearing capacity, widespread infrastructure damage affecting 91% of residents, and effective demonstration of accelerated deterioration under high precipitation conditions through the Markov chain model. The developed framework provides a practical tool for proactive infrastructure management, enabling early identification of vulnerable sections and optimal timing of maintenance interventions. The integration of technical analysis with community experiences creates a holistic approach that considers both engineering requirements and user needs.

Future applications should focus on expanding the framework to additional locations, incorporating climate change projections, and developing dynamic modeling capabilities. The integration of advanced materials research and economic analysis will further enhance the framework's utility for sustainable infrastructure development.

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