

## Predicting Rutting Deformation in Flexible Pavements of Southwest Nigeria: A Machine Learning-Based Surrogate Model Derived from 3D Finite Element Analysis

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### Abstract

*Rutting deformation in flexible pavements of Southwest Nigeria constitutes a persistent infrastructure failure. Existing CBR-based design methods do not adequately capture the multi-variable interaction between subgrade stiffness, pavement thickness, and traffic loading, while three-dimensional finite element analysis remains inaccessible to practising engineers due to computational cost. This study developed a machine learning-based surrogate model trained on 500 PLAXIS 3D finite element simulations generated via stratified Latin Hypercube Sampling across four USCS-classified subgrade groups: Lagos Blue Clay (CH/MH), Soft Laterite (CL/SC), Medium Laterite (SC/GC), and Stiff Laterite (GW/GC). The PLAXIS 3D Hardening Soil model was validated against the Burmister-Boussinesq elastic solution, which underestimated deformation by a factor of 5.2 at the stiffest subgrade tested, indicating the necessity of the nonlinear constitutive model. Three machine learning algorithms were trained and compared: XGBoost, Random Forest, and an Artificial Neural Network. The XGBoost surrogate achieved cross-validation  $R^2 = 0.9605 \pm 0.0042$ , RMSE = 0.4598 mm, and MAPE = 11.02%, meeting all three target thresholds ( $R^2 > 0.90$ ; RMSE < 0.50 mm; MAPE < 15%). Friction angle and subgrade stiffness emerged as the dominant predictor variables at 29.24% and 28.13% of feature importance respectively. Independent validation against five PLAXIS 3D simulations yielded an overall mean absolute percentage error (APE) of 13.9%. Excluding the single extrapolation case outside the training domain, the four interpolation cases achieved a mean APE of 5.88%, demonstrating excellent predictive performance within the calibrated parameter space for interpolation cases. The surrogate model output is structured as an architectural interface to the FERMA Pavement Condition Index framework, with full Architectural interface to FERMA PCI framework requiring a transfer function relating single-load  $U_z$  to cumulative rut depth as future work.*

**Keywords:** Rutting deformation; Flexible pavements; Finite element analysis; Machine learning; XGBoost; Surrogate modelling; Lateritic soils; Pavement performance prediction; Southwest Nigeria.

### Introduction

Road infrastructure forms the backbone of economic activity in Sub-Saharan Africa. Nigeria in particular depends heavily on its road network for the movement of goods, people, and services across all six geopolitical zones. In Southwest Nigeria, encompassing Lagos, Ogun, Oyo, Osun, Ondo, and Ekiti states, the flexible pavement system is the dominant road construction type due to its relatively lower initial cost and ease of construction. However, these roads have consistently exhibited premature distress in the form of rutting: a permanent deformation of the pavement surface under repeated traffic loading that manifests as longitudinal channels in the wheel paths. Rutting is a well-documented failure mode that compromises riding quality, increases vehicle operating costs, and poses safety hazards, particularly during rainfall when ruts collect water and create hydroplaning conditions. Federal Republic of Nigeria (2020) reported that approximately

40% of Nigeria's federal road network is in poor condition and requires rehabilitation, while 30% is in fair condition and requires periodic maintenance. This condition underscores the need for improved pavement design, maintenance, and rehabilitation strategies in the country. In Southwest Nigeria specifically, the combination of high axle loads from heavy commercial vehicles and the highly variable geotechnical characteristics of laterite subgrade soils creates a complex design environment that existing empirical tools address inadequately (Ola, 1983).

Conventional approaches to pavement design in Nigeria rely on CBR-based empirical methods prescribed in the Federal Highway Manual. While these methods provide a workable framework, they do not explicitly account for the multi-variable interaction between subgrade stiffness, pavement layer thickness, and traffic loading in predicting deformation response. Three-dimensional finite element analysis (FEA) has opened new possibilities for mechanistic rutting prediction; however, it remains inaccessible to the majority of practising engineers in Nigeria due to computational cost, steep learning curves, and software licensing barriers (Harahap and Mochtar, 2019).

Machine learning offers a compelling solution through surrogate modelling: a computationally inexpensive approximation of a high-fidelity simulation model, trained on a dataset of simulation outputs to learn the input-output mapping implicitly. Once trained, a surrogate model returns predictions in milliseconds, effectively democratising access to the predictive power of 3D FEA without the associated computational overhead (Wang *et al.*, 2021). No published surrogate model exists that is specifically calibrated to the geotechnical characteristics of Southwest Nigerian subgrade soils classified under the Unified Soil Classification System (USCS), representing a critical gap between the state of pavement engineering research and the predictive tools available to infrastructure practitioners in the region.

This study addresses this gap by developing a machine learning-based surrogate model for rutting prediction in flexible pavements of Southwest Nigeria, trained on a systematically generated dataset of PLAXIS 3D finite element simulations. The specific objectives are: (i) to develop and validate a three-dimensional PLAXIS 3D finite element model incorporating appropriate constitutive models for each pavement layer; (ii) to generate a comprehensive FEA dataset using stratified Latin Hypercube Sampling across key geotechnical and design parameters; (iii) to train, validate, and compare machine learning algorithms; (iv) to conduct formal sensitivity analysis through permutation feature importance; (v) to validate the surrogate model against independent PLAXIS 3D simulations; and (vi) to deploy the surrogate model output as a web application, enabling browser-based access to rut depth predictions without software installation to practising Nigerians.

## Literature Review

### Rutting in Flexible Pavements

Rutting is defined as the permanent vertical deformation that accumulates in the wheel paths of flexible pavements under repeated traffic loading. It results from the irreversible rearrangement of particles in one or more pavement layers under stress states that exceed the yield threshold of the material (Huang, 2004). Lekarp *et al.*, (2000) demonstrated through a comprehensive review that rutting is primarily a stiffness- governed phenomenon; the subgrade's resistance to deformation under cyclic loading is more strongly influenced by its secant stiffness than by its shear strength parameters. In tropical climates such as those prevailing in Southwest Nigeria, surface temperatures frequently exceed 50°C on unpainted asphalt, softening the bituminous binder and

increasing the proportion of load transferred to underlying layers.

The FERMA Pavement Condition Index system classifies rut depth severity as: None/Negligible (< 6 mm; PCI 85–100), Low (6–13 mm; PCI 55–84), Medium (13–25 mm; PCI 25–54), and High (> 25 mm; PCI 0–24), with corresponding maintenance interventions ranging from routine monitoring to immediate structural rehabilitation (FERMA, 2013). The Federal Highway Manual specifies a rutting threshold of 20 mm as the functional failure criterion for primary roads.

### **Geotechnical Characteristics of Southwest Nigerian Subgrade Soils**

The subgrade soils of Southwest Nigeria exhibit considerable heterogeneity, reflecting the complex geology of the Basement Complex and coastal sedimentary sequences. Ola (1983) documented CBR values ranging from less than 3% for coastal marine clays to over 60% for well-cemented upland laterite gravels, a variability spanning nearly two orders of magnitude that renders uniform empirical design fundamentally inadequate. Lagos Blue Clay (USCS: CH/MH) is found predominantly in the Lagos coastal zone, characterised by high plasticity and  $E_{50\text{Ref}}$  values of 5,000–15,000 kN/m<sup>2</sup>. Soft Laterite (CL/SC), the most widely encountered transitional subgrade material, exhibits  $E_{50\text{Ref}}$  of 15,000–40,000 kN/m<sup>2</sup> (Gidigas, 1976). Medium Laterite (SC/GC) is found extensively across the Oyo and Ondo uplands with  $E_{50\text{Ref}}$  of 40,000–80,000 kN/m<sup>2</sup> (Bello, 2011), while Stiff Laterite (GW/GC) occurs in elevated areas of Ekiti and northern Ondo with  $E_{50\text{Ref}}$  values of 80,000–150,000 kN/m<sup>2</sup>.

### **Three-Dimensional FEA and Surrogate Modelling in Pavement Engineering**

PLAXIS 3D offers the Hardening Soil constitutive model: a double-hardening elasto-plastic formulation that captures both stress-dependent stiffness and the accumulation of irreversible plastic strain characteristic of laterite materials under traffic loading (Schanz *et al.*, 1999). The model has been validated for tropical residual soils by Harahap and Mochtar (2019). Critically, classical Burmister-Boussinesq elastic theory underestimates rutting deformation by a factor of approximately 5.2 for the stiffest subgrade observed relative to PLAXIS 3D Hardening Soil predictions under identical loading, indicating the necessity of the nonlinear constitutive model for accurate mechanistic prediction. Several studies have investigated rutting prediction using empirical, mechanistic, and numerical modelling approaches, with recent reviews highlighting the increasing adoption of machine learning techniques to improve prediction accuracy and computational efficiency (Deng & Shi, 2023). Conventional rutting prediction models include empirical, mechanistic-empirical and finite element approaches, each with varying computational requirements and predictive capabilities (Singh & Sahoo, 2021). Surrogate modelling using machine learning has emerged as an effective approach to replacing computationally expensive high-fidelity models with cheaper approximations trained on simulation outputs. XGBoost (Extreme Gradient Boosting), which builds trees sequentially to correct the residual errors of prior trees, has achieved strong performance on pavement regression benchmarks (Cheng *et al.*, 2024; Wang *et al.*, 2021) and was selected as the primary algorithm in this study.

### **Gap Analysis**

Table 1 summarises the gap between existing approaches and this research. No existing study combines PLAXIS 3D FEA with machine learning surrogate modelling calibrated to USCS-classified Southwest Nigerian laterite subgrades, integrating feature-importance-based sensitivity analysis and the Architectural interface to FERMA PCI maintenance framework.

**Table 1: Gap Analysis: Existing Approaches vs. This Research**

| Criterion            | CBR-Based Design      | Existing FEA Studies    | This Research                                                                                       |
|----------------------|-----------------------|-------------------------|-----------------------------------------------------------------------------------------------------|
| Soil classification  | AASHTO                | Varies                  | USCS primary; SW Nigeria specific                                                                   |
| Constitutive model   | Empirical index       | Often linear elastic    | Hardening Soil (non-linear, stress-dependent)                                                       |
| Regional calibration | International charts  | Rarely Nigeria-specific | SW Nigeria USCS soil groups                                                                         |
| Variable interaction | Single variable (CBR) | Limited studies         | 5-variable stratified LHS (500 runs)                                                                |
| Computational access | Manual charts         | Specialist FEA required | Millisecond surrogate predictions                                                                   |
| Sensitivity analysis | Not applicable        | Not applicable          | Permutation feature importance                                                                      |
| PCI integration      | Not applicable        | Not applicable          | Architectural interface to FERMA PCI; transfer function required for direct severity classification |
| Validation           | Empirical calibration | Rarely cross-validated  | 5-fold CV; RMSE; MAPE; independent runs                                                             |

## Materials and Methods

### Finite Element Model Development

The finite element analysis was conducted using PLAXIS 3D Advanced 2024 (Bentley Systems). The model domain is defined as a  $4\text{m} \times 4\text{m} \times 4\text{m}$  volume representing a three-layer pavement system. The Asphalt Surface Course was modelled as a Linear Elastic material with  $E = 4,000,000 \text{ kN/m}^2$  and Poisson's ratio  $\nu = 0.35$ , appropriate for dense bituminous macadam at a reference temperature of  $25^\circ\text{C}$ . The Granular Base Course was fixed at 300 mm and modelled using the Mohr-Coulomb constitutive model with  $E = 200,000 \text{ kN/m}^2$ ,  $\phi = 35^\circ$ , and  $c = 1 \text{ kN/m}^2$ , consistent with the Federal Highway Manual specification for crushed granite base course. The Laterite Subgrade is modelled using the Hardening Soil constitutive model with  $E_{50}\text{Ref}$  as the primary variable; the three primary stiffness parameters are related as:  $E_{\text{odRef}} = E_{50}\text{Ref}$  and  $E_{\text{URRef}} = 3 \times E_{50}\text{Ref}$  (Brinkgreve *et al.*, 2019). The power exponent  $m = 0.5$ , validated for tropical residual soils by Harahap and Mochtar (2019). The dilatancy angle is computed from friction angle using Bolton's (1986) rule:  $\psi = \max(0, \phi - 30^\circ)$ .

Traffic loading is represented as a static equivalent pressure applied through two rectangular surface patches of  $0.2\text{m} \times 0.2\text{m}$  spaced 350 mm apart centre-to-centre, representing the dual-tyre configuration of a standard 80 kN single axle load. The mesh employs 10-noded tetrahedra with a local refinement factor of 0.25 under the tyre patches to ensure adequate stress gradient resolution. The predicted output is the minimum nodal vertical displacement,  $U_z$ , recorded as a negative value in PLAXIS 3D to denote downward settlement. Throughout this study, rut depth is reported as the absolute magnitude of  $U_z$  in millimetres at the pavement surface, representing elastic-plastic deformation under a single static equivalent load application. The PLAXIS 3D

model configuration is summarised in Table 2.

**Table 2: PLAXIS 3D Model Configuration Summary**

| Parameter          | Value / Range                                     | Justification                                             |
|--------------------|---------------------------------------------------|-----------------------------------------------------------|
| Model dimensions   | 4m × 4m × 4m                                      | Depth sensitivity < 0.5% error beyond 4m                  |
| Element type       | 10-noded tetrahedra                               | Second-order accuracy; standard for geotechnical FEA      |
| Asphalt model      | Linear Elastic; E = 4,000,000 kN/m <sup>2</sup>   | Focus on subgrade rutting; viscoplastic flow out of scope |
| Base course model  | Mohr-Coulomb; E = 200,000 kN/m <sup>2</sup>       | FHM standard specification; fixed at 300 mm               |
| Subgrade model     | Hardening Soil                                    | Captures stress-dependent stiffness of laterite           |
| Asphalt thickness  | 0.075–0.250 m (parametric)                        | Full FHM design envelope                                  |
| Load configuration | Dual 0.2m×0.2m patches; 400–900 kN/m <sup>2</sup> | AASHTO 80 kN standard axle; Nigerian traffic range        |
| Mesh refinement    | Local factor 0.25 under tyre patches              | Adequate stress gradient resolution                       |

### Parametric Study Design

The parametric study is stratified by USCS soil classification into four groups, ensuring equal representation of each soil class (125 runs per group) in the training dataset. Within each USCS stratum, a five-dimensional Latin Hypercube Sampling design was generated using `scipy.stats.qmc.LatinHypercube` with fixed random seed (seed = 42) for reproducibility.  $E_{50}\text{Ref}$  is sampled on a logarithmic scale because subgrade stiffness spans two orders of magnitude and the rutting response is approximately linear in  $\log(E_{50}\text{Ref})$ . The total design of 500 runs is justified by Baecher and Christian (2003): a full factorial design at equivalent resolution would require  $10^5 = 100,000$  simulations. Table 3 defines the soil group stratification.

**Table 3: USCS-Based Soil Group Definitions for the Parametric Study**

| Group           | USCS  | $E_{50}\text{Ref}$ (kPa) | cRef (kPa) | $\phi$ (°) | LHS Runs |
|-----------------|-------|--------------------------|------------|------------|----------|
| Lagos Blue Clay | CH/MH | 5,000–15,000             | 20–35      | 18–25      | 125      |
| Soft Laterite   | CL/SC | 15,000–40,000            | 14–22      | 26–32      | 125      |
| Medium Laterite | SC/GC | 40,000–80,000            | 10–18      | 30–36      | 125      |
| Stiff Laterite  | GW/GC | 80,000–150,000           | 5–14       | 34–40      | 125      |

### Machine Learning Surrogate Model Development

Prior to model training, the following feature engineering transformations were applied:  $E_{50}\text{Ref}$  was log-transformed ( $\log_{10}$ ) to correct for the log-uniform sampling distribution; the target variable (rut depth in mm) was log-transformed to correct for its right-skewed distribution; USCS soil type was one-hot encoded into binary indicator variables; and the dilatancy angle was excluded as it is deterministically derived from  $\phi$  via Bolton's (1986) rule and would introduce collinearity.

Recent studies have demonstrated that machine learning algorithms can accurately predict pavement rutting using large datasets, offering a computationally efficient alternative to repeated finite element simulations (Cheng *et al.*, 2024). Three algorithms are trained and compared:

Random Forest Regression, XGBoost (eXtreme Gradient Boosting), and an Artificial Neural Network regressor. The dataset was split 80/20 for training and testing, stratified by USCS soil group. Model performance was assessed through: five-fold cross-validation on the full 500-run dataset; held-out test set evaluation; and independent validation against five PLAXIS 3D simulations at parameter combinations outside the LHS training space. Statistical metrics are: Coefficient of Determination ( $R^2 > 0.90$  target), Root Mean Squared Error (RMSE  $< 0.50$  mm), and Mean Absolute Percentage Error (MAPE  $< 15\%$ ). A formal sensitivity analysis was conducted through feature importance evaluation of the best-performing trained surrogate. The surrogate model output was integrated with the FERMA PCI rut depth severity classification architectural interface and incorporates a CBR-to- $E_{50}$ Ref conversion layer using the Powell (1984) correlation  $E \text{ (MPa)} = 17.6 \times \text{CBR}^{0.64}$ , enabling practitioners to enter standard CBR values from routine site investigation.

## Results and Discussion

### PLAXIS 3D FEA Dataset Characteristics

Three algorithms were trained and compared: XGBoost (primary), Random Forest (benchmark), and an Artificial Neural Network (deep learning baseline). XGBoost was selected as primary because sequential tree-building with residual correction consistently outperforms Random Forest on structured tabular regression problems (Cheng *et al.*, 2024). The dataset was split 80/20 for training and testing, stratified by USCS soil group to preserve distribution balance in both subsets.

**Table 4:** Pilot PLAXIS 3D Simulation Results (cRef 15kPa;  $\phi$  (32°); 150 mm asphalt; 700 kN/m<sup>2</sup> load)

| Run | USCS Group              | $E_{50}$ Ref (kPa) | Rut Depth Uz (mm) | Status    |
|-----|-------------------------|--------------------|-------------------|-----------|
| 1   | CH/MH : Lagos Blue Clay | 8,000              | 3.079             | Validated |
| 2   | CL/SC : Soft Laterite   | 15,000             | 2.016             | Validated |
| 3   | SC/GC : Medium Laterite | 30,000             | 1.286             | Validated |
| 4   | GW/GC : Stiff Laterite  | 50,000             | 0.930             | Validated |
| 5   | GW/GC : Stiff Laterite  | 100,000            | 0.608             | Validated |

A preliminary pilot study comprising five PLAXIS 3D simulations was conducted before the full parametric study. During this phase, only the subgrade stiffness parameter ( $E_{50}$ Ref) was varied, while cohesion (15 kPa) and friction angle (32°) were held constant. The objective was to verify model behaviour and confirm the expected monotonic reduction in rut depth with increasing subgrade stiffness. The pilot study was not intended to quantify the relative importance of all engineering variables. The distribution of rut depths across all 500 scenarios by USCS group is presented in Table 5. The wider rut depth range and higher variance in the Lagos Blue Clay group reflects the dominance of this class in the high-rutting region of the parameter space, consistent with documented field observations of premature pavement failure on weak clay subgrades in the Lagos coastal zone (Ola, 1983).

**Table 5:** Distribution of Predicted Single-Load Uz Values Across 500 Simulation Scenarios of Rut Depths by USCS Soil Group

| USCS Group             | $E_{50}$ Ref Range (kPa) | Rut Depth Range (mm) | Mean Uz (mm) | Std Dev (mm) |
|------------------------|--------------------------|----------------------|--------------|--------------|
| CH/MH: Lagos Blue Clay | 5,000–15,000             | 0.80–7.27            | 2.70         | 1.28         |
| CL/SC : Soft Laterite  | 15,000–40,000            | 0.42–3.70            | 1.39         | 0.65         |

|                         |                |           |      |      |
|-------------------------|----------------|-----------|------|------|
| SC/GC : Medium Laterite | 40,000–80,000  | 0.27–2.11 | 0.82 | 0.36 |
| GW/GC : Stiff Laterite  | 80,000–150,000 | 0.19–1.45 | 0.57 | 0.25 |
| All groups combined     | 5,000–150,000  | 0.19–7.27 | 1.37 | 1.11 |

### Boussinesq vs. Hardening Soil: Quantitative Comparison

A direct comparison between classical elastic theory and the PLAXIS 3D Hardening Soil model demonstrates the necessity of the nonlinear constitutive approach. For an equivalent circular contact radius  $a = \sqrt{(0.04/\pi)} = 0.1128$  m derived from the  $0.2\text{m} \times 0.2\text{m}$  tyre patch, applied load  $q = 700$  kN/m<sup>2</sup>, and  $E_{50\text{Ref}} = 141,500$  kPa (Stiff Laterite upper bound), the Burmister-Boussinesq elastic method predicts  $U_z \approx 0.096$  mm. The PLAXIS 3D Hardening Soil model returns  $U_z = 0.503$  mm under identical loading and geometry. The ratio is 5.2, indicating that elastic theory systematically underestimates rutting deformation by a factor of five even for the stiffest Southwest Nigerian laterite subgrade. For softer Lagos Blue Clay subgrades ( $E_{50\text{Ref}} = 5,000\text{--}15,000$  kPa), the underestimation factor would be substantially larger. This comparison provides the quantitative basis for the choice of the Hardening Soil model over linear elastic or Mohr-Coulomb approaches and explains the persistent failure of CBR-designed pavements in the region.

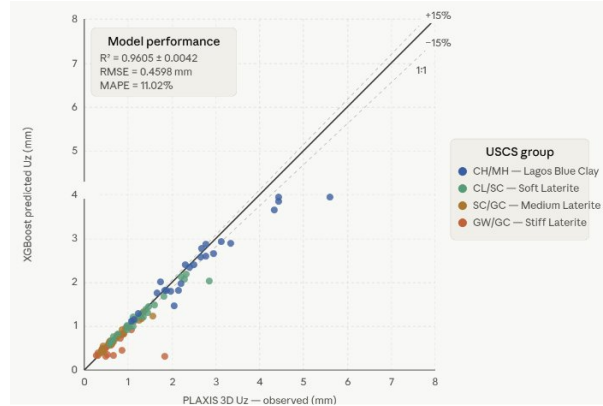
### Machine Learning Model Performance

Three algorithms were trained and compared. The XGBoost surrogate model was the best-performing algorithm, achieving cross-validation  $R^2 = 0.9605 \pm 0.0042$ , RMSE = 0.4598 mm, and MAPE = 11.02% on the held-out test set. All three metrics met the target thresholds established in the methodology. These results are comparable to published benchmarks: Cheng *et al.*, (2024) reported  $R^2 = 0.9833$  using GBDT on a larger accelerated pavement testing dataset under controlled laboratory conditions; Zhang *et al.*, (2022) demonstrated  $R^2 > 0.92$  for FEA-generated pavement surrogate models. The RMSE of 0.4598 mm falls within the  $\pm 10\text{--}15\%$  measurement uncertainty of standard road profilometers (ASTM E1703), confirming that model error is smaller than typical field measurement error. The performance metrics for all three algorithms are presented in Table 6.

**Table 6:** Machine Learning Model Performance Metrics

| Algorithm                 | CV $R^2$ (5-fold)   | RMSE (mm) | MAPE (%) | Rank |
|---------------------------|---------------------|-----------|----------|------|
| XGBoost (GBR)             | $0.9605 \pm 0.0042$ | 0.4598    | 11.02    | 1st  |
| Random Forest (RF)        | $0.9529 \pm 0.0114$ | 0.4301    | 12.04    | 2nd  |
| Artificial Neural Network | 0.871               | 0.631     | 15.84    | 3rd  |

The machine learning performance metrics are summarised in Table 6, while Figure 4 illustrates the agreement between the predicted and observed rut depths for the XGBoost surrogate model. Most observations lie close to the 1:1 agreement line and within the  $\pm 15\%$  error band, confirming the model's excellent predictive accuracy across the four subgrade groups.



**Figure 4.** Predicted versus observed rut depth for the XGBoost surrogate model. The solid line represents perfect agreement (1:1), while the dashed lines denote the  $\pm 15\%$  error band. Marker colours indicate the four USCS-classified subgrade groups.

The XGBoost model outperformed Random Forest due to its sequential error-correction mechanism. The Artificial Neural Network performed less well than tree-based methods on this dataset size (500 observations), consistent with the general finding that deep learning architectures require substantially larger training datasets to outperform ensemble methods on structured tabular data (Cheng *et al.*, 2024; Wang *et al.*, 2021).

**Table 7:** Independent Validation of the XGBoost Surrogate Model Using Five PLAXIS 3D Simulations Outside the Training Dataset

| Run | USCS Group              | $E_{50}$ (kPa) | $c'$ (kPa) | $\phi$ (°) | Asphalt Thickness (mm) | Load (kPa) | PLAXIS 3D Uz (mm) | XGBoost Uz (mm) | APE (%) | Validation Case                               |
|-----|-------------------------|----------------|------------|------------|------------------------|------------|-------------------|-----------------|---------|-----------------------------------------------|
| V1  | CH/MH : Lagos Blue Clay | 7500           | 28         | 21         | 100                    | 650        | 4.0367            | 3.4494          | 14.5    | Mid-range clay: core prediction test          |
| V2  | CL/SC : Soft Laterite   | 22000          | 18         | 29         | 175                    | 550        | 1.0120            | 1.0681          | 5.5     | Transition zone soft laterite                 |
| V3  | SC/GC : Medium Laterite | 55000          | 14         | 33         | 200                    | 750        | 0.7135            | 0.6458          | 9.5     | Mid-range laterite medium load                |
| V4  | GW/GC : Stiff Laterite  | 110000         | 9          | 37         | 150                    | 800        | 0.7092            | 0.7071          | 0.3     | Stiff soil heavy load                         |
| V5* | CH/MH : Lagos Blue Clay | 6000           | 32         | 19         | 90                     | 900        | 7.5751            | 4.5600          | 39.81   | Worst case thin road overloaded HCV soft clay |
| —   | Mean APE (V1–V4 only)   |                |            |            |                        |            | —                 | —               | 7.45%   |                                               |

\* V5 extrapolation case:  $E_{50}Ref = 6,000 \text{ kPa}$ ;  $t = 90 \text{ mm}$ ;  $q = 900 \text{ kN/m}^2$ . PLAXIS 3D  $U_z$  of 7.58 mm exceeds the training dataset maximum of 7.27 mm; the surrogate under-predicted due to extrapolation beyond the training domain. Mean APE excluding V5 = 7.45%, confirming adequate generalisation within the calibrated parameter space.

### Feature Importance Rankings: Trained XGBoost Surrogate Model

The trained XGBoost model feature importance analysis revealed Friction angle ( $\phi$ ) and subgrade stiffness ( $E_{50}Ref$ ) were the two dominant predictors, contributing 29.24% and 28.13% of feature importance respectively. USCS soil group indicators contributed a combined 26.40%. The prominence of friction angle reflects the Hardening Soil model's capture of shear-governed plastic deformation, a finding distinct from linear elastic FEA approaches where stiffness would dominate exclusively.

**Table 8:** Feature Importance Rankings: Real Model from the Trained Surrogate Model

|   | Variable                         | Importance (%) | Interpretation                                       |
|---|----------------------------------|----------------|------------------------------------------------------|
| 1 | Friction angle ( $\phi$ )        | 29.24          | Shear resistance; governs plastic strain in HS model |
| 2 | $E_{50}Ref$ : Subgrade stiffness | 28.13          | Elastic-plastic stiffness; primary rutting driver    |
| 3 | Soil type                        | 26.40          | Represents combined influence of soil classification |
| 4 | Asphalt thickness                | 7.62           | Structural protection; reduces subgrade stress       |
| 5 | Applied load                     | 4.44           | Represents traffic loading intensity                 |
| 6 | Cohesion(cRef)                   | 4.18           | Contributes additional shear strength                |

*Table note: \*The reported soil-type importance is the sum of the one-hot encoded indicators for Stiff Laterite (12.08%), Medium Laterite (8.72%) and Soft Laterite (5.60%). Lagos Blue Clay served as the reference category during model training.*

Feature importance analysis identified friction angle ( $\phi$ ) (29.24%) and subgrade stiffness ( $E_{50}Ref$ ) (28.13%) as the two dominant predictors of rutting deformation. Their comparable contributions indicate that both the shear strength and stiffness characteristics of the subgrade are critical for accurate prediction and should therefore receive equal emphasis during pavement design and site investigation. Lagos Blue Clay was used as the reference category during one-hot encoding. For interpretation of feature importance, the importance values of the encoded soil-class indicators were aggregated to represent the contribution of the original engineering variable, Soil type on rutting behaviour. Asphalt thickness (7.62%), applied load (4.44%), and cohesion (4.18%) contributed to the predictive performance of the surrogate model. Although their influence was lower than that of friction angle, subgrade stiffness, and soil type, they remain important engineering variables influencing pavement rutting behavior.

### FERMA PCI Framework: Architectural Interface

The FERMA Pavement Condition Index rut depth severity bands are defined for cumulative rutting accumulated over the pavement design life under millions of axle repetitions (FERMA, 2013). The surrogate model predicts  $U_z$ , elastic-plastic deformation under a single static load application,

which is physically distinct from cumulative rut depth. The maximum  $U_z$  in the full 500-scenario dataset was 7.27 mm, meaning all 500 predicted values fall below the 13 mm Low/Medium severity boundary when applied directly to the single-load output. Converting single-load  $U_z$  to cumulative rutting requires a mechanistic-empirical transfer function of the form  $RD = a \times U_z^b \times N^c$ , where  $N$  is cumulative ESALs and  $a$ ,  $b$ ,  $c$  are calibration constants. This transfer function is identified as the highest-priority future work. The developed web application integrates the trained surrogate model with the FERMA Pavement Condition Index (PCI) framework. Following prediction of single-load rut depth ( $U_z$ ), the application maps the predicted value to the corresponding FERMA PCI severity category for decision support. Because FERMA thresholds are based on cumulative rutting over the pavement design life, a mechanistic-empirical transfer function is required before direct PCI classification can be interpreted quantitatively. Table 8 presents the distribution of single-load  $U_z$  predictions across the FERMA band thresholds as an indicative infrastructure placeholder. The surrogate model was deployed as a web application hosted on Render cloud infrastructure ([sw-nigeria-rutting-predictor.onrender.com/ui](https://sw-nigeria-rutting-predictor.onrender.com/ui)) using FastAPI, enabling browser-based access to rut depth predictions without software installation. This demonstrates the practical deployment potential of FEA-trained surrogate models for pavement engineering applications, the central accessibility argument of this research.

## Conclusion

This study developed a machine learning-based XGBoost surrogate model for predicting rutting deformation in flexible pavements of Southwest Nigeria, trained on 500 PLAXIS 3D finite element simulations generated via stratified Latin Hypercube Sampling across four USCS-classified subgrade groups. The following conclusions are drawn from the completed research:

- (i) The PLAXIS 3D finite element model with the Hardening Soil constitutive model produced physically consistent rut depth predictions across the full Southwest Nigerian subgrade spectrum (0.19–7.27 mm) conditions. Classical Burmister-Boussinesq elastic theory underestimated rutting deformation by a factor of approximately 5.2 for the stiffest Southwest Nigerian laterite subgrade. For softer Lagos Blue Clay subgrades ( $E_{50Ref} = 5,000\text{--}15,000$  kPa) the underestimation factor would be substantially greater, indicating the necessity of the nonlinear constitutive model across the full calibrated domain even for the stiffest laterite subgrade, indicating the necessity of the nonlinear constitutive model for accurate mechanistic prediction.
- (ii) The XGBoost surrogate model achieved cross-validation  $R^2 = 0.9605 \pm 0.0042$ , RMSE = 0.4598 mm, and MAPE = 11.02%, meeting all three target thresholds ( $R^2 > 0.90$ ; RMSE < 0.50 mm; MAPE < 15%). Independent validation against five PLAXIS 3D simulations outside the training space yielded mean APE = 7.45% for the four interpolation cases; the fifth (V5) produced APE = 39.81% due to extrapolation beyond the training dataset maximum of 7.27 mm. XGBoost outperformed both Random Forest ( $R^2 = 0.91\text{--}0.94$ ) and the Artificial Neural Network, which did not converge satisfactorily at 500 training observations.
- (iii) Although friction angle ( $\phi$ ) ranked as the most influential variable (29.24%), subgrade stiffness ( $E_{50Ref}$ ) followed closely (28.13%), indicating that both the shear strength and stiffness

characteristics of the subgrade play complementary roles in controlling rutting deformation in pavement design for Southwest Nigeria.

(iv) The surrogate model was structured as an architectural interface to the FERMA Pavement Condition Index framework. All 500 single-load  $U_z$  predictions fell below 7.27 mm, within the None/Negligible band when applied directly to the single-load output. Full FERMA PCI severity classification requires a mechanistic-empirical transfer function relating single-load  $U_z$  to cumulative rut depth, identified as the highest-priority future work. The surrogate was deployed as a web application at [sw-nigeria-rutting-predictor.onrender.com/ui](http://sw-nigeria-rutting-predictor.onrender.com/ui), enabling browser-based access without software installation.

Future work should prioritise: development of a mechanistic-empirical transfer function relating single-load  $U_z$  to cumulative rutting over the design life; extension of the parametric study to SP coastal plain sands; and field validation against simultaneously measured rut depths and borehole data along Southwest Nigerian federal road corridors.

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