Terrain- and Meteorological Influences on Path Loss for Mobile Networks in Bwari Area Council, Abuja: A Systematic Review and Meta-Analysis

Dr. Waheed M. Audu[1], Dr. Kufre E. Jack[2], Jibrin, Ogwu Isaac[3]

[1,3]Department of Telecommunication Engineering, Faculty of Engineering Federal University of Technology, Minna.

[2]Department of Mechatronics Engineering, Faculty of Engineering, Federal University of Technology, Minna.

DOI: https://doi.org/10.51583/IJLTEMAS.2026.150300094

Received: 01 April 2026; Accepted: 06 April 2026; Published: 18 April 2026

ABSTRACT

The design and optimization of mobile communication networks depend heavily on accurate path loss prediction, especially in settings with complicated topography and changing meteorological conditions. The predicted accuracy of traditional empirical propagation models, such Hata and COST-231, is limited in heterogeneous situations since they mainly take distance and antenna parameters into consideration, frequently ignoring the combined impact of topographical variability and weather conditions. This study presents the empirical development of a terrain–meteorological path loss model for mobile networks in Bwari Area Council, Abuja, Nigeria. By combining important climatic factors like temperature, relative humidity, and rainfall with topography descriptors like elevation, building density, and vegetation, the suggested model expands upon the traditional log-distance formulation. Multiple linear regression techniques were employed to estimate model parameters after field measurements of received signal strength were gathered in various propagation settings. Improved statistical performance indicators, such as lower root mean square error (RMSE) and higher coefficient of determination (R2), show that the addition of environmental factors considerably improves prediction accuracy when compared to traditional models. The developed model is especially well-suited for deployment in tropical and heterogeneous environments because it successfully captures both spatial and temporal fluctuations in signal transmission. By offering an experimentally verified, environment-aware approach that enhances path loss prediction and facilitates effective mobile network planning and optimization, the study advances propagation modeling. For improving coverage estimation and network performance in comparable geographic areas, the suggested model provides a scalable method.

Keywords: Path loss, mobile network, Bwari Area Council, terrain, meteorology

INTRODUCTION

The need for precise path loss prediction, which is crucial for effective network planning, coverage optimization, and quality-of-service assurance, has increased due to the quick growth of mobile communication networks. The accuracy of path loss models, which offer a mathematical depiction of signal attenuation as electromagnetic waves travel over space, has a direct impact on the dependability of mobile network deployment. However, in complex and heterogeneous environments, especially in tropical regions where environmental variability significantly affects signal propagation, the applicability of traditional empirical models like Okumura–Hata and COST-231 is frequently limited [1,2].

In Nigeria, topography features like elevation, building density, and vegetation, along with climatic elements like temperature, humidity, and rainfall, have a significant impact on mobile network propagation. Additional attenuation mechanisms, including diffraction, scattering, and air absorption, are introduced by these environmental characteristics and are not sufficiently represented by conventional models. According to recent research, prediction accuracy is greatly increased when topographical and atmospheric factors are included in

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue III, March 2026

propagation models, especially in urban and suburban settings [3,4]. Furthermore, the necessity for environment-specific propagation models that can handle high-frequency signal behavior and dynamic atmospheric effects has increased due to the growing deployment of advanced mobile technologies, such as LTE and forthcoming 5G systems. Due to their capacity to incorporate environmental factors and enhance prediction performance beyond conventional empirical formulations, data-driven and hybrid modeling approaches have consequently drawn attention [5,6].

Despite these developments, research in Nigeria is still mostly localized and dispersed, with little attempt made to systematically synthesize or compare model performance in various contexts. Furthermore, there is a lack of standardized methods for assessing terrain- and weather-aware models, and the incorporation of meteorological variables into path loss modeling is still inconsistent. The creation of transferable and universal propagation models for mobile network planning in Nigeria is hampered by this fragmentation.

This article offers a comprehensive evaluation and meta-analysis of path loss models for mobile networks in Nigeria that are reliant on geography and weather in order to close this gap. The paper evaluates model performance using established statistical measures, summarizes previous empirical and data-driven research, and investigates the degree to which environmental influences improve forecast accuracy. It is anticipated that the results will offer a solid foundation for the creation of environment-specific, adaptive path loss models appropriate for the deployment of tropical mobile networks.

METHODOLOGY

In order to compile the available data on path loss models for mobile networks in Nigeria that are reliant on weather and geography, this study uses a systematic review and meta-analysis technique. Transparency, repeatability, and methodological rigor are ensured by conducting the review in compliance with PRISMA 2020 standards [7].

LITERATURE REVIEW

Path Loss Modeling in Mobile Networks

Path loss represents the attenuation of electromagnetic signal strength as it propagates from a transmitter to a receiver and remains a fundamental parameter in mobile network design. Accurate path loss prediction is essential for coverage estimation, interference management, and network optimization. Conventional empirical models such as Okumura–Hata, COST-231, and Egli have been widely adopted due to their simplicity and low computational requirements. However, their predictive performance is often limited when applied to heterogeneous environments that differ significantly from the conditions under which they were originally developed [2,8]. The shortcomings of conventional models have become increasingly noticeable as mobile communication technologies, especially LTE and 5G systems, have advanced. More adaptive modeling techniques that can capture nonlinear and environment-specific propagation features are needed for higher frequency bands and complicated propagation settings [6]. Because of this, hybrid and data-driven models that incorporate environmental factors into path loss prediction have received more attention in recent years.

Terrain Effects on Signal Propagation

One of the main factors affecting radio wave propagation in mobile networks is terrain features. Through processes including diffraction, reflection, and scattering, factors like elevation, irregular topography, building density, and vegetation cover have a substantial impact on signal attenuation. Path loss varies significantly across different terrain types, especially across urban, suburban, and rural areas, according to empirical research done in Nigeria [5]. Additional research has demonstrated that adding terrain descriptors to path loss models significantly increases forecast accuracy. For example, by taking into account changes in topography and ambient clutter, terrain-adaptive modeling techniques have been demonstrated to perform better than traditional empirical models [9]. Similarly, topography variability affects the route loss exponent and adds to seasonal variations in signal attenuation, according to recent research conducted in Southwestern Nigeria [1]. These

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue III, March 2026

results highlight how crucial terrain-aware modeling is to producing accurate propagation forecasts, especially in areas with a variety of topographical characteristics like Nigeria.

Meteorological Effects on Signal Propagation

Signal propagation is more variable due to meteorological circumstances, particularly in tropical regions like Nigeria. Rainfall, humidity, temperature, and air pressure are important meteorological factors that impact path loss. Through processes like absorption, scattering, and variations in air refractivity, these elements affect signal attenuation [9]. Signal loss at higher frequencies, such as those utilized in LTE and 5G systems, has been found to be significantly influenced by rainfall in particular [10].

Temperature and humidity also have an impact on signal propagation by changing the atmosphere's dielectric qualities, which in turn affects the parameters of wave transmission. According to empirical research done in Zaria, Nigeria, atmospheric characteristics have a major effect on model performance and GSM signal propagation [11]. Despite these results, many current models continue to ignore weather-related effects, and the incorporation of meteorological variables into path loss modeling is still inconsistent.

Path Loss Modeling in Nigeria

Many Nigerian locations, including Abuja, Lagos, Akure, Kaduna, and Onitsha, have conducted extensive research on path loss modeling. The majority of research concentrates on assessing and improving traditional empirical models for regional settings. For instance, studies on mobile networks and digital terrestrial television in Nigeria showed that standard models frequently need to be calibrated in order to provide acceptable prediction accuracy [5]. Path loss modeling for upcoming 5G networks in Nigerian cities has also been the subject of recent research, which has shown that topography and urban density have a major impact on signal propagation at higher frequencies [5].

The significance of environment-specific modeling was also highlighted by research conducted in Southern Nigeria that found differences in path loss exponent values between urban and rural settings [4]. It is challenging to create unified models that can be used in many Nigerian contexts because the majority of these research are site-specific and lack generalizability.

Emerging Trends: Hybrid and Data-Driven Models

Hybrid and machine learning-based path loss models have been developed as a result of recent developments in wireless communication research. These models combine data-driven methods such random forest algorithms, support vector machines (SVM), and artificial neural networks (ANN) with empirical formulations.

Research has demonstrated that machine learning techniques can more accurately predict outcomes than conventional models by capturing intricate nonlinear interactions between environmental factors and signal attenuation [11,12]. Additionally, for mobile network planning, hybrid models that integrate environmental data with physical propagation theory are becoming more and more popular. These methods have benefits, but they also have drawbacks in terms of data accessibility, computational complexity, and model interpretability.

Research Gap

Path loss modeling in Nigeria has advanced significantly, however there are still a number of important gaps. First, there is little integration of both aspects in a single modeling framework; instead, the majority of research concentrate on either topographical or meteorological effects separately. Second, most current models are not scalable across various environments and are site-specific.

Third, despite its varied topography and climate, little research has been done expressly on Bwari Area Council, Abuja. These gaps underscore the necessity of creating a path loss model that takes into account both weather and terrain in order to enhance prediction accuracy and facilitate dependable mobile network planning.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue III, March 2026

Comparative synthesis of existing studies on terrain-and meteorological dependent path loss modeling

A comparative summary of previous research on terrain- and weather-dependent path loss modeling is shown in Table 1, which highlights important factors, approaches, conclusions, constraints, and highlighted research gaps.

Table 1. Summary of Literature on Terrain and Meteorological Effects on Path Loss in Mobile Networks

Author(s) & Year	Study Area	Model Type	Key Variables Considered	Methodology	Key Findings	Limitations
Akinbolati et al. [5]	Nigeria (multiple locations)	Empirical (Okumura–Hata variants)	Terrain (urban, suburban, rural)	Field measurements and model evaluation	Conventional models require calibration for Nigerian environments	Limited meteorological consideration
Isabona et al. [9]	Medium-sized cities	Hybrid (terrain-adaptive model)	Elevation, terrain irregularity	Nonlinear regression modeling	Terrain-based adaptation improves prediction accuracy	Weather parameters not included
Akinbolati & Abe [1]	Southwestern Nigeria	Empirical (optimized models)	Terrain, seasonal variation	Comparative model analysis	Path loss varies with terrain and season (wet vs dry)	Limited integration of atmospheric data
Isabona et al. [9]	Tropical regions	Theoretical/ Analytical	Temperature, humidity, atmospheric pressure	Atmospheric propagation modeling	Meteorological parameters significantly affect signal propagation	Lack of field validation
Budalal et al. [10]	Outdoor environments	Empirical/ Analytical	Rainfall, frequency	Model-based analysis	Rainfall significantly increases attenuation at higher frequencies	Limited focus on terrain
Umar et al. [13]	Zaria, Nigeria	Empirical (GSM models)	Temperature, humidity, pressure	Field measurements and statistical analysis	Atmospheric parameters influence signal strength and model accuracy	Limited terrain integration
Chimezie et al. [4]	Southern Nigeria	Empirical (LTE models)	Environment (urban vs rural)	Path loss exponent analysis	Path loss varies significantly across environments	No weather integration
Afape et al. [3]	Nigerian cities (Abuja, Lagos, etc.)	Empirical (mmWave models)	Terrain, urban density	Field measurements (5G frequencies)	High-frequency propagation strongly influenced by environment	Limited meteorological variables

The synthesis shows that the majority of previous research either concentrates on the effects of geography or weather separately, with little attempt made to combine the two into a single modeling framework. Additionally, a significant gap in the creation of generic, environment-adaptive path loss models is highlighted by the

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue III, March 2026

dominance of site-specific models and the restricted use of machine learning techniques with local datasets. These gaps support the need for a propagation model specifically designed for the Bwari Area Council in Abuja that takes weather and geography into account.

Classical and Empirical Path Loss Models

In mobile communication systems, accurate signal attenuation prediction depends on the use of proven propagation models. These models serve as the basis for contemporary wireless network planning and offer mathematical frameworks for evaluating path loss under various environmental situations. Although the complexity, assumptions, and applicability of classical and empirical path loss models vary, they both provide crucial information about how radio waves behave in various environments and at various frequencies.

Free Space Path Loss (FSPL) Model

The simplest basic propagation model is the Free Space Path Loss (FSPL) model, which describes signal attenuation in perfect line-of-sight (LoS) conditions free from scattering, diffraction, and obstruction [14]. It offers a theoretical foundation for assessing more intricate models.

$$FSPL\ (dB) = 20log_{10}(d) + 20log_{10}(f) + 20log_{10}\left(\frac{4\pi}{\lambda}\right) \qquad 1$$

Where d = Distance between transmitter and receiver (meters), f = Signal frequency (Hz), λ = Wavelength (m) calculated as $\lambda = \frac{c}{f}$, c = Speed of light in vacuum ($3 \times 10^8\ m/s$)

For practical application:

$$FSPL\ (dB) = 20log_{10}(d_{km}) + 20log_{10}(f_{MHz}) + 32.44 \qquad 2$$

Where d_{km} = Distance in kilometers, f_{MHz} = Frequency in MHz

Despite its simplicity, the FSPL model can be used as a guide for actual propagation analysis in open rural areas with little obstacle.

Log-Distance Path Loss Model

By adding a path loss exponent (n) to account for environmental factors such obstructions and irregular terrain, the Log-Distance Path Loss model expands on the FSPL concept [15].

$$PL(d) = PL(d_0) + 10nlog_{10}\left(\frac{d}{d_0}\right) + X_\sigma \qquad 3$$

Where PL(d) = Total path loss at distance d (in dB), PL(d_0) = Reference path loss at a reference distance d_0 (in dB), n = Path loss exponent (environment-dependent) which depends on the terrain type (urban areas typically have $n = 3\ to\ 5$, and rural areas may have $n = 2\ to\ 3$), d = Distance between transmitter and receiver (meters or kilometers), d_0 = Reference distance (typically 1 m for indoor, 100 m/1 km for outdoor) and X_σ = Shadowing term (zero-mean Gaussian random variable with standard deviation σ, in dB). A simplified form of the Log-Distance Path Loss model, without considering the shadowing term, is presented in Equation 4

$$\text{PL(d)} = PL(d_0) + 10nlog_{10}\left(\frac{d}{d_0}\right) \qquad 4$$

This model is widely used due to its adaptability across different environments, with the exponent n varying depending on terrain characteristics.

Hata Model

The Hata model is an empirical formulation designed for urban, suburban, and rural environments within the

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue III, March 2026

frequency range of 150–1500 MHz [15].

$$PL_{Hata} = 69.55 + 26.16log_{10}(f) - 13.82log_{10}(h_b) - a(h_m) + [44.9 - 6.55log_{10}(h_b)]log_{10}(d) \quad 5$$

Where f: Frequency (MHz), h_b: Base station height (m), h_m: Mobile station height (m), d: Distance (km) and $a(h_m)$: Correction factor for the mobile antenna height, given by Equation 6.

$$a(h_m) = (1.1log_{10}(f) - 0.7)h_m - (1.56log_{10}(f) - 0.8) \quad 6$$

It incorporates antenna height correction factors and provides reliable predictions for large-scale propagation in built environments.

COST-231 Hata Model

By extending the Hata formulation to higher frequencies (1500–2000 MHz), the COST-231 Hata model makes it appropriate for contemporary mobile communication systems [16].

$$PL_{COST} = PL_{HATA} + C \quad 7$$

Where $C = 3$ dB for urban areas, $C = 0$ dB for suburban/rural

This model is particularly relevant for urban and suburban deployments in contemporary cellular networks.

Okumura Model

Based on extensive field measurements, the Okumura model is a semi-empirical method that includes correction factors for antenna characteristics and terrain [5].

$$PL_{Okumura} = PL_{FSPL} + A_{\mu}(f, d) - G(h_b) - G(h_m) - G_{area} \quad 8$$

Where $A_{\mu}(f, d)$: Median attenuation from Okumura graphs (empirical), $G(h_b)$: Base station gain factor, $G(h_m)$: Mobile station gain factor and G_{area}: Gain based on terrain type (urban, suburban, open). Its flexibility allows application across diverse environments, although it requires empirical data for accurate calibration.

Log-Normal Shadowing Model

The Log-Normal Shadowing model accounts for stochastic variations in signal strength due to environmental obstructions such as buildings and vegetation [4].

$$\mathrm{PL_{LN}(d)} = PL_0 + 10nlog_{10}(d) + X_{\sigma} \quad 9$$

Where PL_0 is the reference path loss at distance d_0, n is the path loss exponent, d is the distance between the transmitter and receiver, X_{σ} is the shadowing factor, which is a random variable with a Gaussian distribution $N(0, \sigma)$, where σ is the standard deviation of the shadowing. This model is particularly effective in urban environments where signal fluctuations are significant.

ITU-R P.1546 and P.1812 Models

The ITU-R P.1546 model incorporates environmental and terrain effects for point-to-area predictions [8]:

$$PL_{ITU1546}(d) = A_{fs} + A_{env} + A_{terrain} \quad 10$$

Where A_{fs} is the free-space path loss, A_{env} accounts for environmental effects such as rain and humidity and $A_{terrain}$ adjusts for terrain effects based on local topography. The enhanced ITU-R P.1812 model further includes diffraction, clutter, and atmospheric attenuation:

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue III, March 2026

$$PL_{P1812} = A_{tot} = A_{free} + A_{diff} + A_{clutter} + A_{atoms} \quad 11$$

Where A_{diff} represents diffraction loss due to terrain obstructions, $A_{clutter}$ accounts for losses caused by buildings and vegetation and A_{atoms} models attenuation due to atmospheric conditions. These models are particularly suitable for complex environments where both terrain and atmospheric conditions significantly influence signal propagation.

Critical Evaluation of Classical Models

Classical path loss models are widely used, although they have a number of drawbacks. The majority of models mainly take into consideration frequency and distance, with little incorporation of environmental factors like topography and weather. Moreover, their empirical character frequently limits its applicability to other geographical areas. These drawbacks emphasize the necessity of adaptive and integrated models that take into account atmospheric and topography factors, especially in tropical regions like Nigeria.

Model Development

Model Formulation

A terrain–meteorological path loss model is created by expanding the traditional log-distance model to include environmental factors pertinent to actual propagation conditions, based on the theoretical framework and practical findings. The traditional log-distance model can be written as follows:

$$\mathrm{PL(d) = PL(d0) + 10nlog10}\left(\frac{d}{d_0}\right) \quad 12$$

To account for environmental effects observed in field measurements, terrain and meteorological correction terms are introduced:

$$PL(d) = PL(d_0) + 10nlog10\left(\frac{d}{d_0}\right) + \Delta_T + \Delta_M \quad 13$$

Substituting the environmental components:

$$PL(d) = PL(d_0) + 10nlog10\left(\frac{d}{d_0}\right) + (\propto_1 E + \propto_2 B + \propto_3 V) + (\beta_1 R + \beta_2 H + \beta_3 T) \quad 14$$

Final Proposed Model

The complete terrain-meteorological path loss model is expressed as:

$$PL(d) = PL(d_0) + 10nlog10\left(\frac{d}{d_0}\right) + \propto_1 E + \propto_2 B + \propto_3 V + \beta_1 R + \beta_2 H + \beta_3 T \quad 15$$

Model Parameters

The table 2 presents the parameters for the

Table 2. Model Parameters

Parameter	Description
PL(d)	Path loss at distance (d) (dB)
PL(d₀)	Reference path loss (dB)
N	Path loss exponent
E	Elevation/terrain irregularity
B	Building density
V	Vegetation density
R	Rainfall intensity

INTERNATIONAL JOURNAL OF LATEST TECHNOLOGY IN ENGINEERING, MANAGEMENT & APPLIED SCIENCE (IJLTEMAS)
ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue III, March 2026

H	Relative humidity
T	Temperature
$\propto_i, \beta_j$	Empirically determined coefficients

Empirical Basis of the Model

The model is based on field measurement data, where observed differences in received signal strength are connected to weather and topography. This formulation improves forecast reliability by capturing actual environmental influences, in contrast to traditional models that mostly rely on distance-based attenuation.

Parameter Estimation

Model parameters are estimated using multiple linear regression analysis, based on measured data:

$$PL_{measured} = PL_{model+\epsilon}$$

The calibration procedure for model parameter estimation is presented in figure 1.

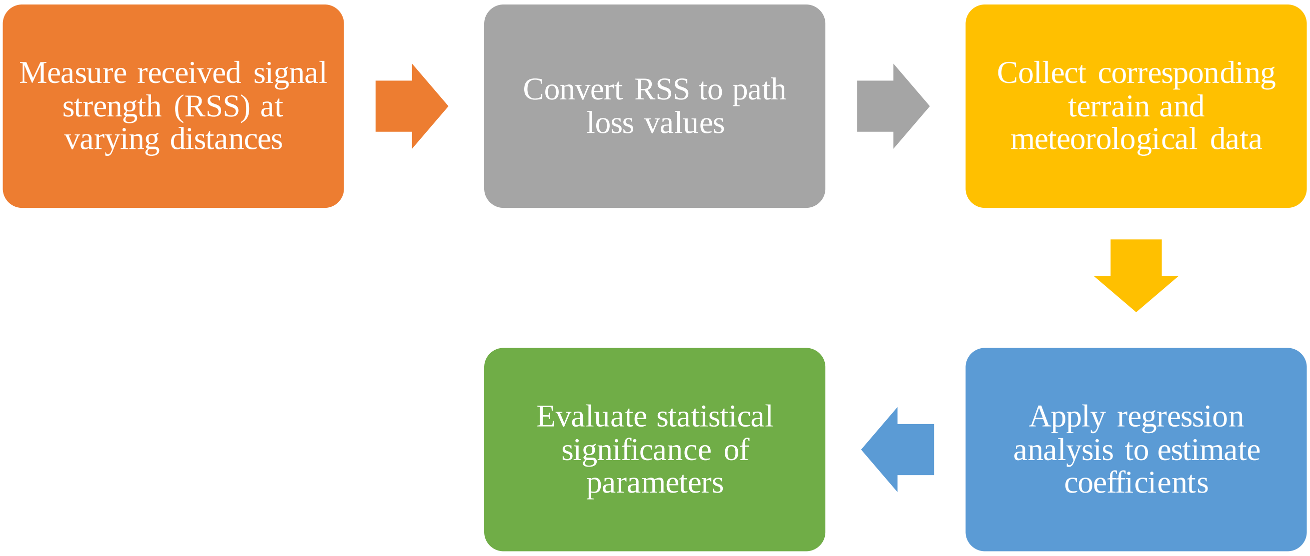

Figure 1. Calibration procedure for model parameter estimation

Model Validation

The developed model is validated using standard statistical metrics:

$$RMSE = \sqrt{\frac{1}{N}\sum\left(PL_{meas} - PL_{pred}\right)^2} \quad 16$$

$$MAE = \frac{1}{N}\sum\left|PL_{meas} - PL_{pred}\right| \quad 17$$

$$R^2 = 1 - \frac{\frac{1}{N}\sum\left(PL_{meas} - PL_{pred}\right)^2}{\sum(PL_{meas} - PL)^2} \quad 18$$

Contributions and Literature-Grounded Justification of the Developed Model

Integrated Treatment of Terrain and Atmospheric Drivers

The created model's integration of meteorological and terrain data into a single path loss formulation is one of its main contributions. This strategy is backed by well-established propagation studies that show that environmental interactions like diffraction, scattering, and atmospheric absorption, in addition to distance-dependent spreading, control signal attenuation [18,19]. Conventional empirical models, such as Hata-based

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue III, March 2026

formulations, offer simplistic approximations that frequently overlook detailed terrain variability and atmospheric dynamics, which limits their usefulness in complicated propagation situations [20]. The created model offers a more physically representative framework for signal propagation analysis by combining meteorological information and terrain characteristics.

Empirical Calibration and Context-Specific Adaptability

The model uses an empirical calibration method where field measurement data is used to estimate the parameters. This approach is in line with earlier research showing that, as compared to generalized empirical formulations, site-specific tuning greatly increases model accuracy [21,22]. The current model reduces prediction error and improves adaptation to the research area by enabling localized parameter estimation, in contrast to traditional models that rely on fixed coefficients generated from various contexts.

Representation of Spatial–Temporal Propagation Dynamics

The model's capacity to capture both temporal and spatial fluctuations in signal propagation is another important contribution. While meteorological variables account for temporal variations brought on by atmospheric conditions, terrain-related parameters reflect spatial variability related to topography and structural density. Given that recent research has shown that atmospheric factors like humidity and rainfall have a substantial impact on signal transmission, particularly in outdoor and tropical settings, this dual representation is especially crucial [22]. As a result, the model offers a more reliable framework for representing propagation dynamics in the real world.

Consistency with Emerging Multi-Variable Modeling Approaches

The significance of including a variety of environmental factors in prediction models is highlighted by recent advancements in wireless propagation modeling. It has been demonstrated that in complex contexts, multi-parameter and hybrid techniques perform better than conventional single-variable models [23]. By combining several environmental parameters into a single empirical formulation, the new model supports this trend by increasing prediction accuracy without sacrificing physical interpretability.

Practical Implications for Mobile Network Planning

The model offers a useful tool for designing and optimizing mobile networks from an application perspective. Improved coverage estimation, more effective base station deployment, and better interference control are all made possible by accurate path loss prediction. These enhancements are essential for contemporary mobile communication systems, as network performance is heavily influenced by environmental variability [24].

Synthesis of Contributions

The created model is supported by existing research showing that multi-variable techniques improve performance in complex environments, locally calibrated models improve prediction accuracy, and environmental factors greatly impact signal propagation. These results lend credence to the creation of a terrain-meteorological path loss model as a reliable and essential development in propagation modeling.

CONCLUSION

This study used an empirical method to create a terrain–meteorological path loss model for mobile networks that incorporates atmospheric and environmental factors into a single propagation framework. By including terrain features and weather circumstances, the model expands on traditional distance-dependent formulations, addressing important drawbacks of traditional empirical models. A more thorough depiction of signal transmission in complicated contexts is made possible by the incorporation of topography and atmospheric factors, especially in areas with diverse landscapes and changing weather patterns. Compared to conventional models that rely on generalized assumptions, the model's predictive reliability is enhanced by using a data-driven calibration approach, which guarantees that its parameters represent actual propagation behavior. The model also

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue III, March 2026

shows how crucial it is to account for both temporal and geographical variability in path loss prediction. While weather conditions introduce time-dependent fluctuations that greatly affect signal behavior in outdoor contexts, terrain variables account for location-dependent attenuation. The robustness and applicability of the model under various propagation conditions are improved by this dual consideration. By offering an environment-aware, experimentally proven approach that enhances path loss prediction accuracy and facilitates effective mobile network planning, the study advances propagation modeling.

REFERENCES

1. Akinbolati, A., & Abe, B. T. (2025, April). Investigating the reliability of empirical path loss models over digital terrestrial UHF channels in Ikorodu and Akure, southwestern Nigeria. In Telecom (Vol. 6, No. 2, p. 28). MDPI.
2. Gündüz, D., Eldar, Y. C., Goldsmith, A., & Poor, H. V. (2022). 1 Machine Learning and Communications: An Introduction. wireless communications, 1, 3.
3. Afape, J. O., Willoughby, A. A., Sanyaolu, M. E., Obiyemi, O. O., Moloi, K., & Dairo, O. F. (2024). Path loss modelling of mmwave outdoor propagation for 5G mobile systems at 28, 38, 60, and 73 GHz in four Nigerian cities. Discover Applied Sciences, 6(10), 495.
4. Chimezie, G. O., Onuchukwu, C. C., & Okereke, N. A. (2024). Determination of Pathloss Exponent 4G LTE Signal in Urban and Rural Environment of Southern Nigeria (Asaba in Delta State and Onitsha in Anambra State). Asian Basic and Applied Research Journal, 6(1), 20-35.
5. Akinbolati, A. M. O. A., & Ajewole, M. O. (2020). Investigation of path loss and modeling for digital terrestrial television over Nigeria. Heliyon, 6(6).
6. Rappaport, T. S., Xing, Y., MacCartney, G. R., Molisch, A. F., Mellios, E., & Zhang, J. (2017). Overview of millimeter wave communications for fifth-generation (5G) wireless networks—With a focus on propagation models. IEEE Transactions on antennas and propagation, 65(12), 6213-6230.
7. Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., ... & Moher, D. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. bmj, 372.
8. Wang, J., Hao, Y., & Yang, C. (2023). The current progress and future prospects of path loss model for terrestrial radio propagation. Electronics, 12(24), 4959.
9. Isabona, J., Imoize, A. L., Ojo, S., Lee, C. C., & Li, C. T. (2022). Atmospheric propagation modelling for terrestrial radio frequency communication links in a tropical wet and dry savanna climate. Information, 13(3), 141.
10. Budalal, A. A., & Islam, M. R. (2023). Path loss models for outdoor environment—with a focus on rain attenuation impact on short-range millimeter-wave links. e-Prime-Advances in Electrical Engineering, Electronics and Energy, 3, 100106.
11. Galvan-Tejada, G. M., & Martinez-Enriquez, A. M. (2025). A machine learning scheme to assess the radio propagation conditions on wireless communication networks. Journal of Ambient Intelligence and Humanized Computing, 16(6), 789-802.
12. Moreno-Cuevas, M., Lorente-López, J., Rodríguez, J. V., Rodríguez-Rodríguez, I., & Sanchis-Borrás, C. (2025). Geospatial Feature-Based Path Loss Prediction at 1800 MHz in Covenant University Campus with Tree Ensembles, Kernel-Based Methods, and a Shallow Neural Network. Electronics, 14(20), 4112.
13. Umar, F. A., Abdu, A. M., Magaji, U. A., Atah, A. Y., Musa, A. G., & Lawan, S. M. (2025). IoT-Enabled Wind Energy Modelling for Irrigation in Rural and Remote Farming Communities of Babura Local Government. Indian Journal of Electrical and Electronics Engineering, 2(3), 01-07.
14. Onipe, J. A. (2021). Path-Loss Prediction Models for Cellular Networks in Okene, Kogi State, Nigeria (Doctoral dissertation).
15. Oladimeji, T. T., Kumar, P., & Oyie, N. O. (2022). Propagation path loss prediction modelling in enclosed environments for 5G networks: A review. Heliyon, 8(11).
16. Joseph, I., Oghu, E., & Roberts, O. O. (2023). Path loss and models: A survey and future perspective for wireless communication networks. International Journal of Advanced Networking and Applications, 15(02), 5892-5907.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue III, March 2026

17. Barrios-Ulloa, A., Ariza-Colpas, P. P., Sánchez-Moreno, H., Quintero-Linero, A. P., & De la Hoz-Franco, E. (2022). Modeling radio wave propagation for wireless sensor networks in vegetated environments: A systematic literature review. Sensors, 22(14), 5285.
18. Durgin, G. D. (2003). Space-time wireless channels. Prentice Hall Professional.
19. Parsons, J. D., & Parsons, P. J. D. (1992). The mobile radio propagation channel.
20. Saunders, S. R., & Aragón-Zavala, A. A. (2024). Antennas and propagation for wireless communication systems. John Wiley & Sons.
21. Abhayawardhana, V. S., Wassell, I. J., Crosby, D., Sellars, M. P., & Brown, M. G. (2005, May). Comparison of empirical propagation path loss models for fixed wireless access systems. In 2005 IEEE 61st vehicular technology conference (Vol. 1, pp. 73-77). IEEE.
22. Crane, R. K. (2003). Propagation handbook for wireless communication system design. CRC press.
23. Isabona, J., Imoize, A. L., Akinwumi, O. A., Omasheye, O. R., Oghu, E., Lee, C. C., & Li, C. T. (2023). Optimal Radio Propagation Modeling and Parametric Tuning Using Optimization Algorithms. Information, 14(11), 621.
24. Andrews, J. G., Buzzi, S., Choi, W., Hanly, S. V., Lozano, A., Soong, A. C., & Zhang, J. C. (2014). What will 5G be?. IEEE Journal on selected areas in communications, 32(6), 1065-1082.