



Seasonal Variation and Machine Learning-Based Prediction of Atmospheric Refractivity over Southwestern Nigeria

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ABSTRACT

Atmospheric radio refractivity strongly influences radio wave propagation, link reliability and signal quality in tropical regions. In south-western Nigeria, pronounced wet and dry seasonal transitions cause large variability in refractivity, yet data-driven predictive tools remain limited. This lack of reliable prediction poses a challenge for communication system planning and performance optimisation in the region. This study investigates the seasonal variation of surface atmospheric refractivity over south-western Nigeria and evaluates the effectiveness of machine learning techniques for its prediction. Four years of meteorological data from an automatic weather station were used to compute refractivity using the Smith–Weintraub formulation. Seasonal and monthly patterns were analysed using descriptive statistics, correlation analysis, and time-series techniques, including trend and anomaly detection. Supervised machine learning models, including Support Vector Regression, Random Forest, Gradient Boosting, and a Multi-Layer Perceptron, were trained to predict daily refractivity from meteorological inputs. Results show seasonal dependence, with higher refractivity during the wet season driven by increased humidity. Among the models, Support Vector Regression achieved the highest predictive accuracy ($R^2 \approx 0.9999$, $RMSE \approx 0.066$), followed by Random Forest. The findings demonstrate that machine learning is a reliable and effective approach for predicting atmospheric refractivity and capturing its seasonal variability in tropical environments.

INTRODUCTION

Atmospheric radio refractivity is a fundamental property that governs the bending, attenuation, and ducting of electromagnetic waves in the lower troposphere (Sheu *et al.*, 2022). Reliable characterisation of refractivity is therefore essential for the design and operation of terrestrial microwave links, broadcast systems, and satellite-to-ground services in the tropics. Refractivity N is commonly expressed using the Smith and Weintraub

formulation, which relates N to surface pressure P , temperature T , and water vapour pressure e :

$$N = 77.6 \frac{P}{T} + 3.73 \times 10^5 \frac{e}{T^2} \quad 1$$

where P = pressure (hPa), T = temperature (K), e = water vapour pressure (hPa).

This expression and its variants remain the basis of international recommendations for radio-propagation practice. Southwestern Nigeria lies within the humid tropical belt and experiences a marked annual cycle with wet and dry seasons,

influenced by the West African monsoon and the Harmattan, respectively (Ibebuchi and Abu, 2023). These seasonal regimes drive large changes in temperature and moisture that directly modulate refractivity and its vertical gradients. National climatological resources describe a single dominant rainy period in Nigeria from roughly April to September or October in the south, and a dry season spanning about November to March, shaped by the north-easterly Harmattan flow (Ishaku *et al.*, 2024). The empirical work of Omotoso and Olajide-Owoyomi (2025) has shown that surface refractivity is typically higher during the wet months when humidity is elevated across Nigeria, with implications for increased ducting probability and path loss variability. Earlier radiosonde and surface-based studies reported clear seasonal cycles in refractivity and its gradients, while more recent local analyses continue to confirm higher N values in the rainy season at southern and central sites (Akpootu *et al.*, 2024). Despite these efforts, comprehensive, data-driven assessments focused on Southwestern Nigeria remain sparse.

At the same time, machine learning (ML) has matured rapidly in atmospheric science, delivering competitive or superior skill to traditional numerical methods for a range of forecasting tasks. This progress suggests that this approach can capture the non-linear dependence of refractivity on local meteorology, offering practical gains for telecom planning and radio-propagation studies in data-limited regions (De Burgh-Day and Leeuwenburg, 2023).

This study investigates the seasonal variation of atmospheric refractivity over Southwestern Nigeria using station-based meteorological data and supervised ML models. We quantify intra-annual patterns of N and evaluate predictive performance across wet and dry seasons. This work aims to update and localise evidence for a region where

reliable propagation planning supports critical infrastructure by combining physically grounded refractivity calculations with modern ML techniques (ITU-R, 2019).

Surface radio refractivity in the lower troposphere controls bending, attenuation, multipath and ducting of microwave links and satellite-to-ground paths (Hao *et al.*, 2022). In tropical West Africa, refractivity varies strongly with moisture and temperature, which in turn vary with the West African monsoon and the Harmattan (Abimbola *et al.*, 2021).

Empirical studies across Nigeria consistently show clear seasonal signatures. Early station and tower measurements at Akure and other southern sites reported higher surface refractivity and super-refractive gradients during the wet season, with an increased probability of ducting and greater path-loss variability (Adediji and Ajewole, 2008). These patterns were tied to seasonal humidity and temperature stratification in the lowest 200 m.

More recent studies in Nigeria have expanded on spatial and temporal coverage using satellite-derived or reanalysis-assimilated meteorological inputs. For example, city-scale assessments in central and southern Nigeria derived monthly and seasonal refractivity from multi-year meteorological datasets and found strong intra-annual variability aligned with the established wet-dry regime (Akinbolati *et al.*, 2024). New mapping efforts by Tanko *et al.* (2025) at the national scale for 2016 – 2020 depict coherent seasonal refractivity fields, with higher N across the southern belt during the monsoon months and lower values during the dry season. These maps highlight the value of refractivity climatologies for communication planning and reinforce the importance of local calibration. Work focused on coastal hubs such as Lagos adds that surface duct conditions are both frequent and meteorologically

controlled, underscoring the risk of anomalous propagation for microwave links in humid marine-influenced settings (Ojo *et al.*, 2024).

The application of machine learning (ML) to refractivity itself is less common than to general weather prediction, but it is growing. Recent work by Shehaj *et al.* (2023) has explored hybrid approaches that combine physical models with ML or geostatistics to generate high-resolution refractivity fields, indicating that data-driven components can capture non-linear relationships among moisture, temperature, and stability that influence N and its vertical gradient. This result suggests that supervised learning can complement classical formulations when high-frequency, local refractivity forecasts are needed for operations.

The most rapid ML advances have occurred in weather forecasting, where models trained on reanalysis outperform or rival leading numerical weather prediction systems for many variables (Lam *et al.*, 2023). GraphCast, FourCastNet, and newer probabilistic models demonstrate skill in medium-range global forecasting and run efficiently (Brewer *et al.*, 2025). While these systems do not predict refractivity directly, their accurate temperature, pressure and humidity fields make them useful upstream drivers for refractivity estimation and ducting risk indices, especially in data-sparse regions.

This literature provides a methodological template for refractivity studies that leverage ML while retaining physical interpretability.

DATA AND METHOD

Data and Study Area

This study utilised meteorological data obtained from the Automatic Weather Station (AWS) shown in Figure 1. It is located at the Department of Pure and Applied Physics, Ladoké Akintola University of

Technology, Ogbomoso, Nigeria (lat.: $\sim 8.13^\circ\text{N}$, long.: $\sim 4.26^\circ\text{E}$, elev.: ~ 347 m). Ogbomoso lies in the south-western climatic belt of Nigeria, a region strongly influenced by the West African monsoon system and characterised by two distinct seasons, namely the wet season (April-October) and the dry season (November-March). This climatic variability directly affects atmospheric thermodynamics and consequently radio refractivity.

The AWS measures multiple meteorological parameters, including air temperature ($^\circ\text{C}$), relative humidity (%), barometric pressure (hPa), wind speed (m/s), and solar radiation (W/m^2). Among these, temperature, humidity, and pressure were the key inputs for computing surface radio refractivity (N) using the widely accepted Smith–Weintraub formulation in Equation 1.

The dataset covers a continuous four-year period from 2012 to 2015, providing sufficient records to capture intra-annual and inter-annual variability. Data logging was done at 5-minute intervals, which allows its aggregation into daily, monthly, and seasonal averages.



Fig 1: AWS at Department of Pure and Applied Physics, LAUTECH

Modelling Approach

The modelling framework adopted in this study was designed to capture the non-linear dependence of surface radio refractivity on meteorological parameters across different seasonal regimes. The approach comprised four main stages: data preprocessing, feature engineering, model training, and performance evaluation.

Data Preprocessing

The raw meteorological data from the LAUTECH AWS were first subjected to quality control procedures. Missing or inconsistent values were handled using interpolation and statistical imputation, while obvious outliers were identified via z-score filtering and removed. The dataset was then aggregated into hourly averages, from which daily, monthly, and seasonal datasets were constructed. This ensured adequate temporal resolution for both descriptive and predictive analysis.

Feature Engineering

Refractivity values (N) were calculated directly from measured temperature, pressure, and humidity, with water vapour pressure e derived from relative humidity and saturation vapour pressure. Additional features such as time indices (month, season), diurnal cycle (hour of day), and interaction terms among meteorological variables were included to enhance model learning. This combination of physical and temporal predictors allowed the models to capture both short-term variability and broader seasonal trends.

Machine Learning Models

Four supervised regression algorithms were considered: Random Forest Regressor (RF), Gradient Boosting Regressor (GBR), Support Vector Regression (SVR), and a feed-forward multi-layer perceptron (MLP) trained with

backpropagation to approximate the highly non-linear refractivity–meteorology mapping.

These algorithms were selected for their proven robustness in atmospheric and meteorological prediction tasks, as demonstrated in recent studies (Bargam *et al.*, 2024; Ghafarian *et al.*, 2022; Meenal *et al.*, 2021; Nadkarni *et al.*, 2023).

Training and Validation

The dataset spanning 2012-2015 was partitioned into training (70%) and testing (30%) subsets using stratified sampling to preserve seasonal balance. A five-fold cross-validation procedure was employed within the training set to tune hyperparameters and reduce overfitting. Grid search and random search optimisation were applied for RF, GBR, and SVR, while the MLP architecture was optimised through iterative experimentation.

Performance Evaluation

Model performance was assessed using three standard regression metrics, which are Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Coefficient of Determination (R^2).

Comparisons were made across both seasonal subsets (wet vs dry) and the overall dataset to evaluate the consistency of predictive performance.

Implementation

All models were implemented in Python (version 3.9) using the Scikit-learn library. Computational experiments were conducted on a laptop with sufficient processing and memory resources to allow efficient hyperparameter tuning.

RESULTS AND DISCUSSION

Relationship between Atmospheric Refractivity and Key Meteorological Parameters

The relationship between atmospheric refractivity N and key meteorological parameters, including air temperature, relative humidity, and air pressure, was

analysed using correlation and graphical methods. The correlation coefficients are presented in Table 1, while Figure 2 illustrates the pairwise relationships between refractivity and each meteorological variable.

As shown in Table 1, atmospheric refractivity exhibited a strong positive correlation with relative humidity ($r = 0.79$) and a moderate negative correlation with air temperature ($r = -0.54$). The relationship with air pressure was relatively weak and positive ($r = 0.29$). These results suggest that

refractivity tends to increase with humidity but decreases with rising temperature.

The scatterplots in Figure 2 reinforce these findings. The plot of refractivity versus temperature shows a clear inverse trend, while refractivity increases steadily with relative humidity. The relationship between refractivity and air pressure is less distinct, consistent with the weaker statistical correlation observed. The results indicate that humidity and temperature are the most influential parameters affecting atmospheric refractivity in the study area, with air pressure exerting a lesser impact.

Table 1: Correlation matrix showing the relationship between atmospheric refractivity N and key meteorological parameters.

Variable	N	AirTemp (°C)	RH (%)	Air pressure (hPa)
N	1.000000	-0.543716	0.792719	0.291776
AirTemp	-0.543716	1.000000	-0.933166	-0.432396
RH	0.792719	-0.933166	1.000000	0.394330
Air pressure	0.291776	-0.432396	0.394330	1.000000

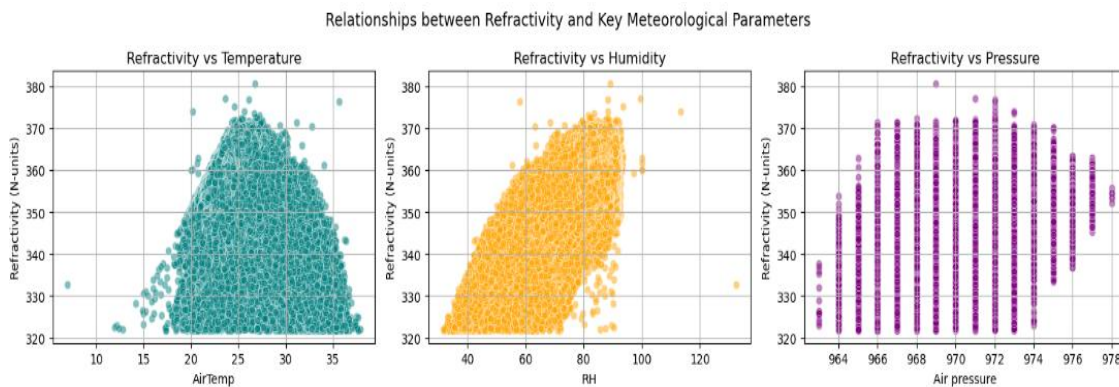


Fig 2: Scatterplots showing the relationship between atmospheric refractivity (N) and (a) air temperature, (b) relative humidity, and (c) air pressure.

Seasonal patterns of refractivity

Seasonal variations in atmospheric refractivity were examined to understand how refractivity fluctuates across wet and dry periods and over the course of

the year. Figure 3a shows that refractivity values are generally higher during the wet season compared to the dry season. This pattern suggests that increased humidity during the wet season contributes to

elevated refractivity, as water vapour plays a significant role in determining atmospheric refractive index. The dry season displays greater variability and a wider interquartile range, indicating more unstable atmospheric conditions.

The monthly mean refractivity values presented in Figure 3b show a clear cyclical pattern, with refractivity increasing steadily from January to June, peaking around midyear, and then declining towards December. This trend aligns with the seasonal climatic cycle, where temperature and humidity jointly influence atmospheric moisture content and, consequently, refractivity.

To further decompose and analyze these fluctuations, a seasonal-trend decomposition using LOESS (STL) was performed (Figure 3c). The observed refractivity component reveals noticeable short-term fluctuations, while the trend component shows a gradual upward movement, peaking around mid-2014 before stabilizing. The seasonal component captures recurring patterns of refractivity variation, reflecting the alternating dry and wet periods across years. The residual component contains minor random fluctuations, indicating that most of the variability in refractivity is well explained by its trend and seasonal components. The results highlight a distinct

seasonal structure in atmospheric refractivity, driven primarily by temperature and humidity dynamics associated with the region’s climatology.

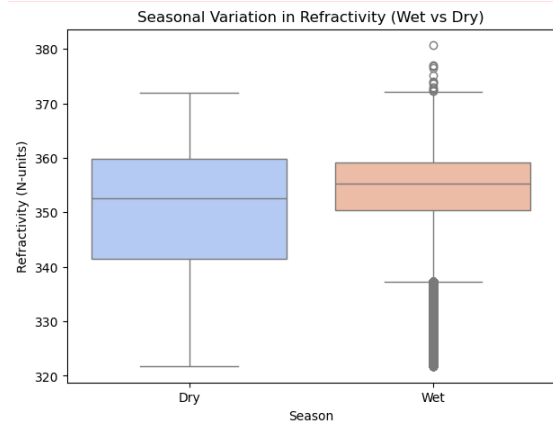


Fig 3a: Seasonal variation in atmospheric refractivity during wet and dry seasons.

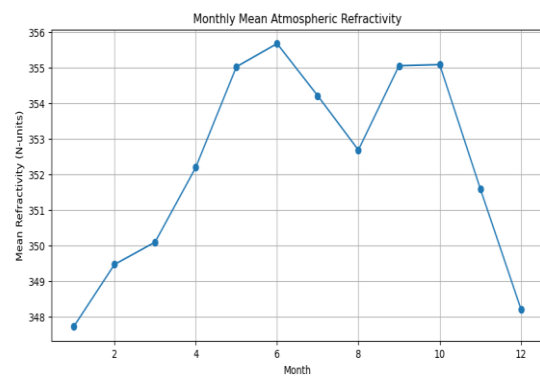


Fig 3b: Monthly mean atmospheric refractivity showing the cyclical pattern across the year.

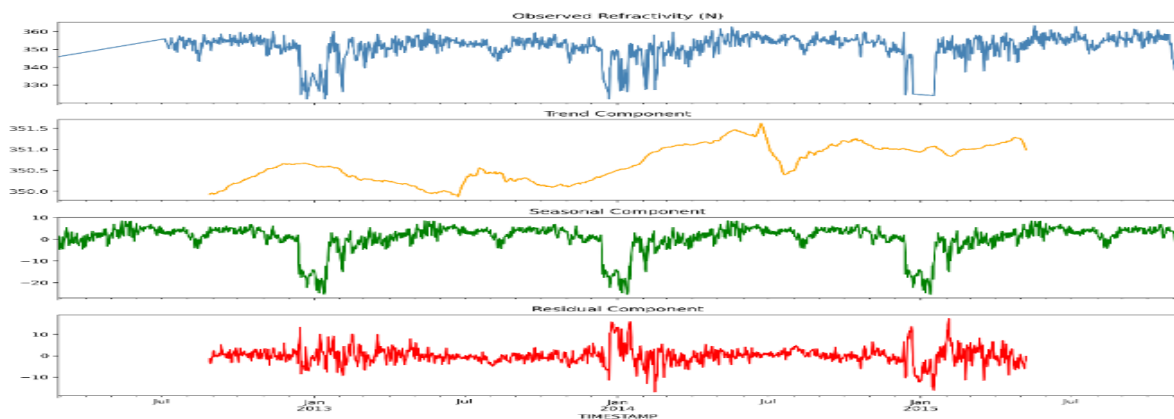


Fig 3c: Seasonal decomposition of atmospheric refractivity (STL) showing observed, trend, seasonal, and residual components.

Trend and Anomaly Detection in Daily Atmospheric Refractivity

Trend Analysis

The linear regression applied to the daily refractivity series yielded a positive slope of approximately 0.0002 N-units per day, equivalent to about 0.07 N-units per year. Although the magnitude is small, the

direction indicates a gradual upward trend in refractivity over the four-year period.

This rise is visually evident in Figure 4b, where the fitted trend line runs slightly above the long-term average from mid-2013 onwards. The trend is consistent with the slow warming and humidity buildup typical of tropical lower-atmosphere conditions.

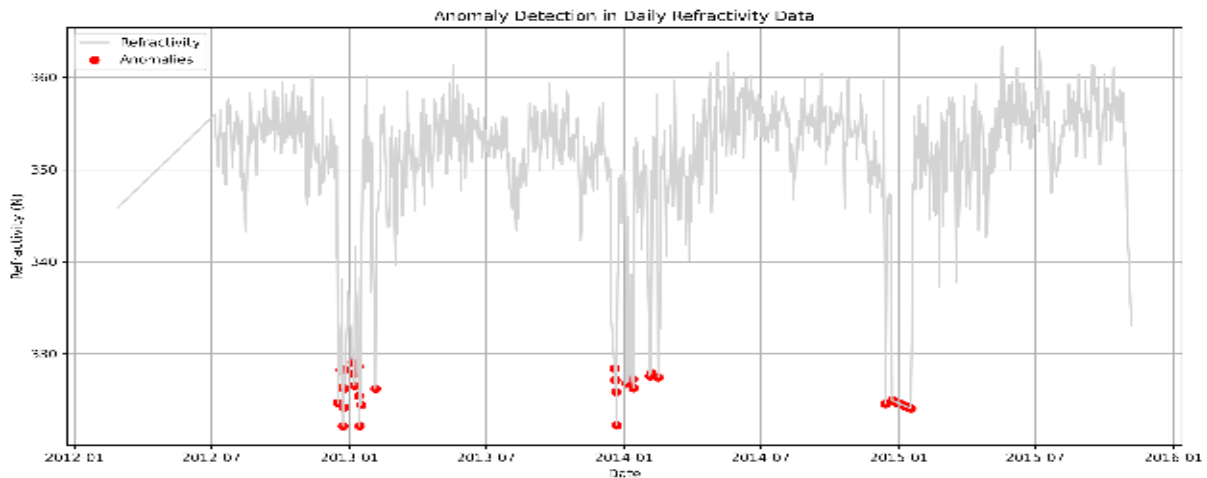


Fig 4a: Daily atmospheric refractivity with detected anomalies

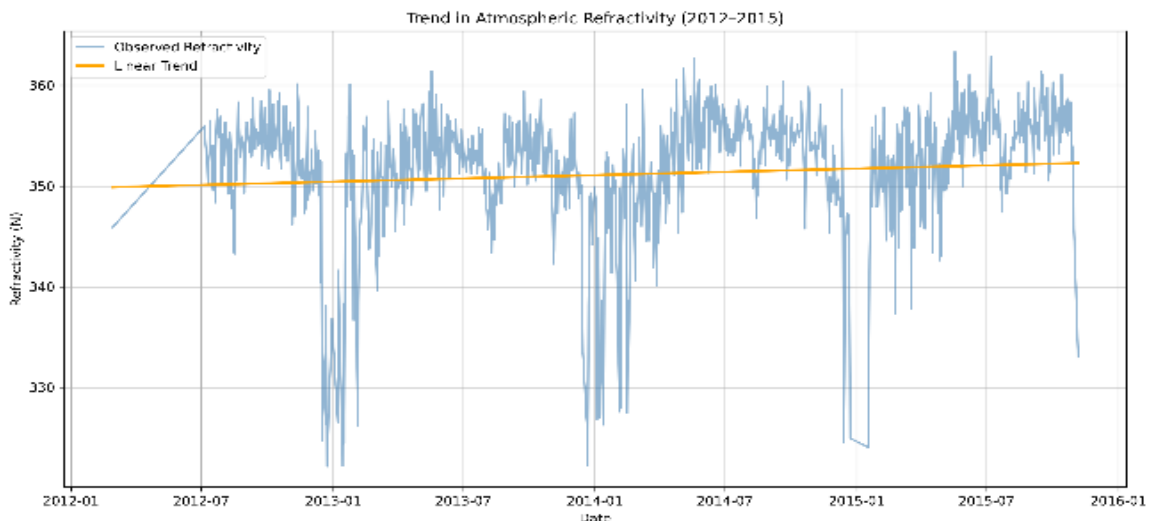


Fig 4b: Long-term trend in daily atmospheric refractivity

Anomaly Detection

Anomalies were identified using a Z-score threshold of $|Z| > 3$ on the daily mean refractivity series. This

approach flagged several extremely low-refractivity events, shown in Figure 4a as red points.

A total of 18 anomalies were detected. Most occurred during mid-year (June – August) and early dry-season months, aligning with periods when sharp temperature drops or sudden moisture intrusions are common.

Several of the extreme dips reached values below 330 N-units, compared with the normal daily range of 340 – 365 N-units. These events likely reflect episodes of rapid atmospheric instability, instrument gaps, or strong refractivity-reducing conditions such as cold surges or dry incursions.

ML prediction performance

The models were evaluated to determine how well they could predict daily atmospheric refractivity, a variable that is highly sensitive to temperature, humidity, and pressure changes. The results show that all four models captured the refractivity pattern with high accuracy, but their performance varied across the error metrics. The Support Vector Regressor (SVR) performed best overall, achieving

the lowest RMSE of 0.066390 and the highest R² of 0.999945, indicating that it explained almost all the variation in refractivity. The Neural Network (MLP) achieved the lowest MAE (0.039567), meaning it produced the smallest average absolute prediction error, although its RMSE was higher (0.223495) compared with SVR and Random Forest.

Random Forest also performed strongly, with an MAE of 0.070335, RMSE of 0.148145, and an R² of 0.999724, showing that it could reliably track day-to-day fluctuations in refractivity. In contrast, Gradient Boosting showed the weakest performance, with a noticeably higher MAE (0.691693) and RMSE (0.969572), and a lower R² (0.988195) compared to the other models.

Overall, the results show that SVR and Random Forest are the most effective models for predicting refractivity in this dataset, offering highly accurate and stable predictions suitable for analysing atmospheric variability.

Table 2: Performance of Machine Learning Models in Predicting Daily Atmospheric Refractivity

Model	MAE	RMSE	R ²
Random Forest	0.070335	0.148145	0.999724
Gradient Boosting	0.691693	0.969572	0.988195
Support Vector Regressor	0.053723	0.066390	0.999945
Multilayer Perceptron	0.039567	0.223495	0.999373

Observed versus Predicted Atmospheric Refractivity

Figure 5 compares observed atmospheric refractivity values with those predicted by the four machine learning models. The dashed 1:1 line represents perfect agreement between observations and predictions. Points lying closer to this line indicate higher predictive accuracy. The SVR shows the strongest alignment with the 1:1 line across the

full refractivity range (approximately 320–380 N-units), indicating excellent agreement between observed and predicted values. This confirms the high R² (0.999945) and low RMSE (0.066) reported earlier, demonstrating that SVR effectively captures both low- and high-refractivity conditions.

Random Forest predictions also closely follow the 1:1 line, particularly within the mid-range refractivity values (330–365 N-units). However, slight dispersion is observed at the lower and upper extremes, suggesting reduced accuracy during extreme atmospheric conditions. This behaviour is consistent with its marginally higher error metrics compared to SVR.

The Neural Network (MLP) model displays a generally linear relationship but with noticeable scatter, especially at higher refractivity values. While its MAE is low, the increased spread around the 1:1 line explains its higher RMSE, indicating sensitivity to outliers and extreme values.

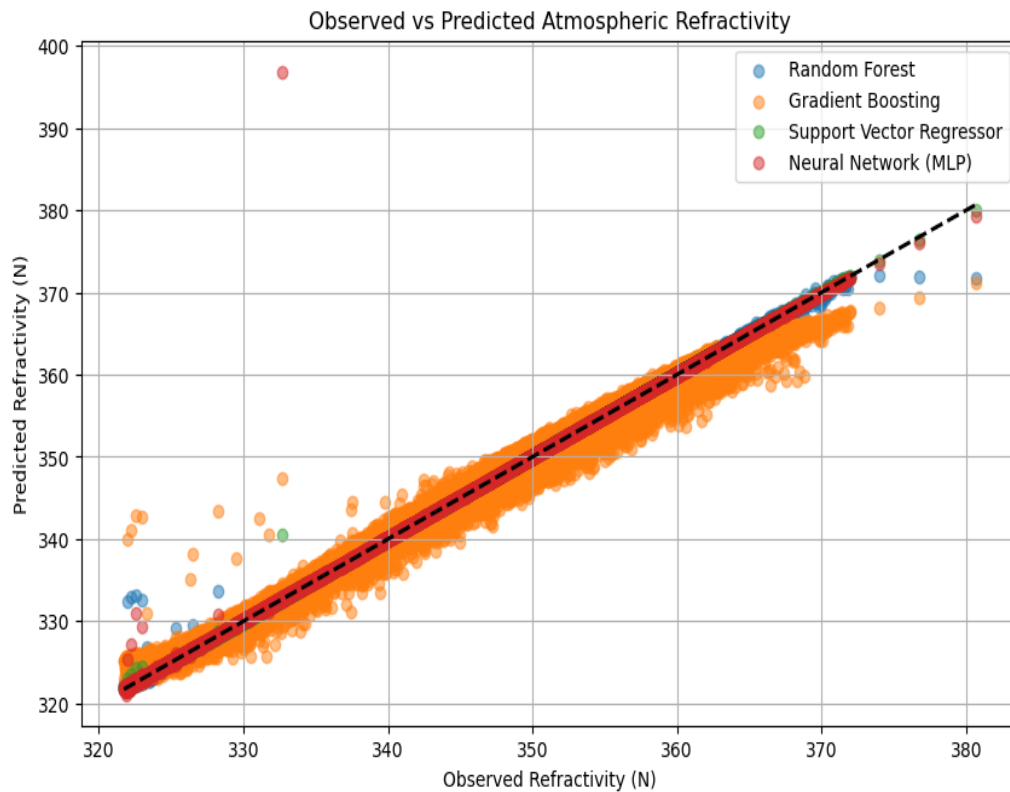


Fig 5: Comparison of Observed and Predicted Atmospheric Refractivity

Gradient Boosting exhibits the largest dispersion from the ideal line, with systematic under- and over-prediction across much of the range. This visual pattern supports its comparatively lower R^2 and higher error values, confirming weaker generalisation performance for this dataset.

The observed–predicted comparison reinforces that SVR provides the most reliable and stable predictions of atmospheric refractivity, followed by Random Forest, while Gradient Boosting performs least effectively. This visual evidence complements

the quantitative performance metrics and supports selecting SVR as the optimal model for refractivity prediction in the study area.

DISCUSSION

The seasonal behaviour of atmospheric refractivity over south-western Nigeria was examined in this study. Also, the capability of machine learning techniques to model and predict their variability was evaluated. The results show that refractivity in the region is strongly influenced by seasonal changes in meteorological conditions, particularly humidity

and temperature, which are dominant during the wet season. Higher refractivity values observed during wet months reflect increased atmospheric moisture content, while lower values during the dry season are consistent with reduced humidity and more stable atmospheric conditions. These findings align with established physical understanding of refractivity dependence on water vapour and pressure in tropical environments.

The seasonal decomposition analysis further revealed a clear annual cycle in refractivity, superimposed on a mild long-term increasing trend. This trend may be associated with gradual changes in regional atmospheric conditions, although its magnitude remains relatively small. The detection of anomalies, mainly during transitional periods between seasons, highlights the dynamic nature of the lower atmosphere and underscores the importance of continuous monitoring for communication and navigation applications.

Beyond characterising refractivity behaviour, a key contribution of this work lies in demonstrating the effectiveness of machine learning techniques for refractivity prediction. Among the models evaluated, SVR showed superior performance, achieving the highest coefficient of determination and lowest prediction error. Its ability to capture complex, non-linear relationships between refractivity and meteorological parameters makes it particularly suitable for modelling atmospheric processes in data-rich environments. Random Forest also performed well, indicating that ensemble-based methods can yield robust predictions, whereas Gradient Boosting showed comparatively weaker performance on this dataset.

The strong agreement between observed and predicted refractivity values confirms that machine learning models can reliably reproduce both seasonal patterns and short-term variations. Overall,

the findings demonstrate that machine learning provides an effective and flexible approach for predicting atmospheric refractivity in south-western Nigeria, offering valuable support for radio propagation studies and the planning of communication systems in low-latitude regions.

CONCLUSION

This study examined the seasonal variation in atmospheric refractivity over south-western Nigeria and evaluated the effectiveness of machine learning techniques for predicting it. The results confirm a clear seasonal pattern, with higher refractivity during the wet season and lower values in the dry season, reflecting the dominant influence of atmospheric moisture. Machine learning models, particularly Support Vector Regression and Random Forest, demonstrated strong predictive capability, accurately capturing both seasonal behaviour and day-to-day variability. The close agreement between observed and predicted refractivity, supported by low error metrics, shows that data-driven approaches can reliably model refractivity in a tropical environment. Overall, the findings demonstrate that machine learning techniques provide an effective and robust framework for predicting atmospheric refractivity, with practical relevance for radio wave propagation, communication system planning, and atmospheric studies in Southwestern Nigeria.

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