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Impact of Climatic Factors on Fertility Behaviour: A Machine Learning Approach

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ABSTRACT
This study investigates the impact of climatic factors temperature, rainfall, and humidity on fertility behaviour across different socio-economic groups in Sokoto State, Nigeria, using Artificial Neural Network (ANN) and Random Forest (RF) machine learning models. Monthly time-series data from 2015 to 2024 covering climatic variables and fertility rates by rural/urban residence and employment status were analyzed. Descriptive statistics, correlation analysis, and time-series decomposition were applied. Predictive models were developed using ANN and RF algorithms, and performance was evaluated using Mean Squared Error (MSE),
Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2). Feature importance analysis identified key climatic predictors. Result shows high variability in rainfall and humidity. Correlation analysis revealed weak positive relationships between climatic variables and fertility, with humidity showing the strongest association. Both models performed poorly, with R^2 values between 0.0021 to 0.0650, though Random Forest (Individual) model slightly outperformed the ANN model. Feature importance analysis consistently identified humidity as the most influential factor across all population groups (Rural, Urban, Employed, Unemployed). Forecasts for 2023-2024 indicated continued disparities, with rural fertility remaining the higher and more variable than urban fertility. Climatic factors, particularly humidity, have a weak but measurable influence on fertility behaviour in Sokoto State. These findings highlight the importance of integrating climatic considerations into public health and demographic planning to mitigate the effects of environmental variability on reproductive outcomes.

Keywords:
Climate,
Fertility Behaviour,
Machine Learning,
Artificial Neural Network,
Random Forest,
Sokoto State, Nigeria.

INTRODUCTION

Fertility behaviour is a critical demographic phenomenon influenced by a complex interplay of socio-economic, cultural, and environmental factors. In regions like Sokoto State, Nigeria, where the economy is predominantly agrarian, climatic conditions such as temperature, rainfall, and humidity are not merely environmental backdrop but active forces shaping livelihoods, health, and consequently, reproductive decisions (Abubakar *et al*., 2023; *Iorsamber*, 2026). Studies have established that climatic stressors can affect fertility through direct physiological pathways, such as heat stress impacting reproductive health, and indirect economic pathways, such as reduced agricultural yield leading to income instability (Rahman *et al*., 2023; Zhang & Bello, 2022).

Sokoto State exhibits significant fertility disparities between its rural and urban populations, and between employed and unemployed groups. Rural and unemployed populations often show different fertility patterns due to factors like agricultural dependence, educational attainment, and access to family planning services (Mohammed *et al*., 2023; Ahmed & Bello, 2021). While the socio-economic determinants of fertility have been extensively studied, the integration of climatic variables into a unified analytical framework remains limited.

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Traditional statistical methods often fall short in capturing the non-linear and complex interactions between climate and fertility (bongaarts,2022). Previous studies found that temperature in northern Nigeria has increased significantly over time, which may influence socio-economic and demographic outcomes. (Akinbolati *et al..2025*).

Machine learning (M L) models, such as Artificial Neural Networks (ANN) and Random Forest (RF), offer powerful alternatives for analyzing such complex datasets. Their ability to model non-linear relationships without prior assumptions about data distribution makes them particularly suitable for this research (Zhang *et al*., 2021; *Tadese et al*., 2025

2023). Despite their potential, the application of these models to demographic studies, especially in the context of climate-fertility interactions in North-western Nigeria, is still nascent.

This study aims to bridge this gap by employing ANN and RF models to assess the combined impact of climatic and socio-economic factors on fertility behaviour in Sokoto State. The specific objectives are:

1. To evaluate the relationship between climatic factors (temperature, rainfall, humidity) and socio-economic fertility patterns.
2. To develop and compare predictive models for fertility behaviour using ANN and RF.

To identify the most influential climatic determinants of fertility through feature importance analysis.

MATERIALS AND METHODS

Study Area and Data Source

This study focused on Sokoto State, located in the semi-arid region of North-western Nigeria. The region is characterized by high temperatures, erratic rainfall, and significant seasonal variations in humidity, making it highly vulnerable to climatic fluctuations.

The study utilized secondary monthly time-series data from 2015 to 2024. Climatic data (minimum temperature, maximum temperature, rainfall, and humidity) were sourced from the Nigerian Meteorological Agency (NiMet) and the World Bank Climate Data. Fertility data, disaggregated into rural, urban, employed, and unemployed categories, were obtained from the Specialist Hospital Sokoto.

Variables

i. **Independent Variables:** Minimum Temperature (°C), Maximum Temperature (°C), Rainfall (mm), Humidity (%).
ii. **Dependent Variables:** Fertility Rate (number of births) for i) Rural, ii) Urban, iii) Employed, and iv) Unemployed populations.

Analytical Framework

The analysis involved three main stages: (1) Exploratory Data Analysis (EDA) including descriptive statistics and time-series decomposition; (2) Predictive modeling using ANN and RF; and (3) Model evaluation and forecasting.

Artificial Neural Network (ANN) Model - Mathematical Equations

A Feedforward Neural Network (FNN) with

Input layer: 3 neurons (Temperature (T), Rainfall (R), Humidity (H)), **Hidden layer:** 1 layer with 5 neurons, **Output layer:** 1 neuron (Fertility (F)), **Activation:** ReLU, **Loss:** Mean Squared Error (MSE), **Optimizer:** Adam.

The hidden layer computation is:

$$h_j = g\left(\sum_{i=1}^{p} w_{ij}\, x_i + b_j\right), \quad j = 1, \dots, q \; [\qquad (1)$$

Where:

x_i = input variables (Temp, Rainfall, Humidity), w_{ij} = weights connecting input (i) to hidden neuron (j), b_j = bias for hidden neuron (j), (p = 3) inputs, (q = 5) hidden neurons, $g(\cdot)$ = ReLU activation, .

$g(z) = \max(0, z)$.

The output neuron is computed as:

$$\hat{F} = \sum_{j=1}^{q} v_j h_j + c \qquad (2)$$

Where:

v_j = weights from hidden layer to output, c = output bias, $\hat{F}$ = predicted fertility.

The general ANN functional mapping is:

$$\hat{F} = f(\mathbf{x};\theta) \qquad (3)$$

Where θ contains all weights and biases.

The loss function minimized during training is:

$$\text{MSE} = \frac{1}{n}\sum_{t=1}^{n}\left(F_t - \hat{F}_t\right)^2 \qquad (4)$$

Random Forest (RF) Model - Mathematical Equations

Random Forest is an ensemble of multiple decision trees trained using bootstrap aggregation and random feature selection.

Bootstrap Sampling

From the training dataset (D), each tree receives a bootstrap sample:

$$D_m \sim \text{Bootstrap}(D), \qquad m = 1, \dots, M \qquad (5)$$

Node Splitting Criterion (Impurity Reduction)

For regression using variance reduction:

$$\Delta I = I(S) - \left(\frac{n_L}{n} I(S_L) + \frac{n_R}{n} I(S_R)\right) \qquad (6)$$

Where:

$I(S)$ = impurity of parent node (variance), S_L, S_R = left and right child nodes, n_L, n_R = sizes of child nodes, n = size of parent node.

Individual Tree Prediction
For tree (m):

$$\hat{F}_m = T_m(x) \quad (7)$$

Random Forest Final Prediction (Regression)

$$\hat{F} = \frac{1}{M}\sum_{m=1}^{M}\hat{F}_m \quad (8)$$

Where:

M is the number of trees, $\hat{F}_m$ is the prediction from each tree/

Feature Importance (Mean Decrease in Impurity)

$$\mathrm{FI}(k) = \sum_{m=1}^{M}\sum_{s\in S_{m,k}}\Delta I_{m,s} \quad (9)$$

Where:

$S_{m,k}$ = set of splits in tree (m) that use feature k, $\Delta I_{m,s}$ = impurity decrease at split s.

Model Evaluation and Performance Metrics

The performance of the ANN and RF models was evaluated using the following metrics:

- Mean Squared Error (MSE) is defined by

$$\text{MSE} = \frac{1}{n}\sum_1^n e_i^2$$

- Root Mean Square Error (RMSE) is defined by

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_1^n e_i^2}$$

- Mean Absolute Error (MAE) is defined by

$$\text{MAE} = \frac{1}{n}\sum_1^n |e_i|$$

- Coefficient of Determination (R^2)

The models were compared based on these metrics to select the best-performing one.

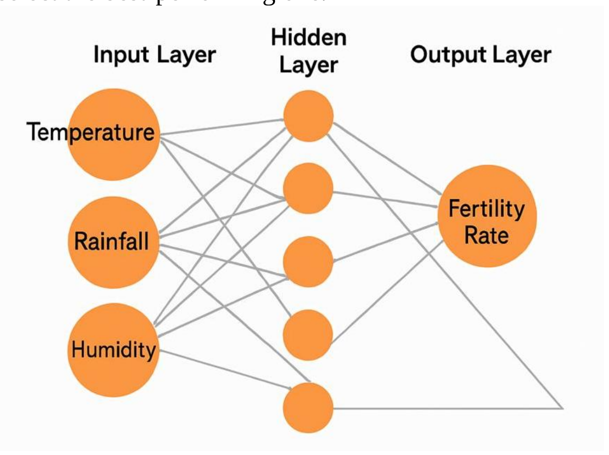

Figure 1: ANN Architecture

A feed-forward Artificial Neural Network was employed to model the relationship between climatic variables and fertility behavior. The input layer consisted of three neurons representing temperature, rainfall, and humidity, one hidden layer containing five neurons, and an output layer with a single neuron representing fertility. The Rectified Linear Unit (ReLU) activation function was applied in the hidden layer to capture nonlinear relationships among variables. The model was trained using the Adam optimizer with Mean Squared Error (MSE) as the loss function. Data were divided into training and testing set to evaluate predictive performance.

The ANN architecture adopted in this study was 3-5-1 structure, which provided a balance between learning capacity and overfitting control for the available dataset.

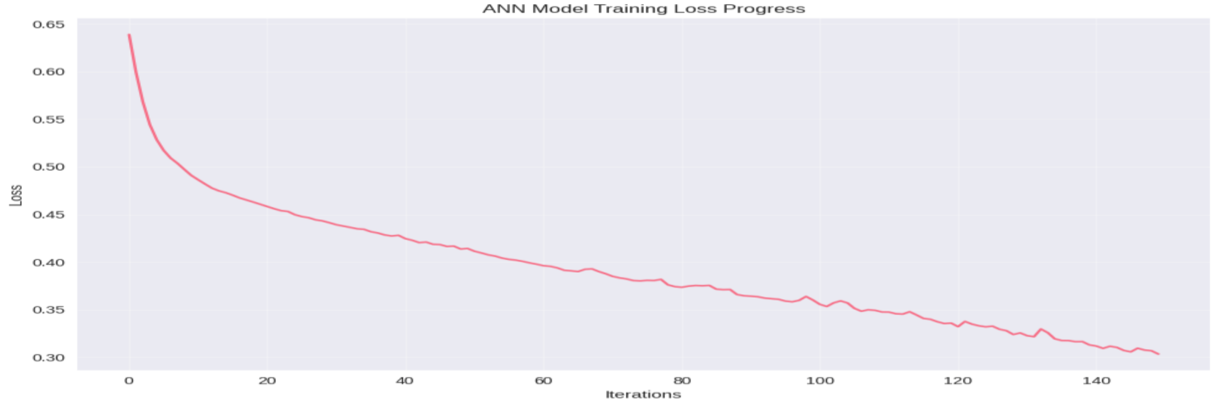

Figure 2: ANN Model Training Progress

The ANN training progress graph shows the model's loss reduction across training epochs, reflecting how well the network minimized prediction errors over time. The curve indicates that the model initially experienced a sharp decline I n loss, demonstrating effective learning in the early stages of training. However, the subsequent plateau suggests that the model quickly reached its capacity and could not further improve prediction accuracy. This training behaviour confirms the earlier evaluation results where the ANN achieved weak predictive performance, implying that the dataset's high variability and limited size constrained the model's ability to capture the complex climate–fertility interactions.

RESULTS AND DISCUSSION

Descriptive Statistics and Exploratory Data Analysis

Interpretation:

The descriptive statistics of the variables are presented in Table 1. Rainfall showed the highest variability (Std. Dev. = 120.86 mm, CV = 1.58), followed by humidity (Std. Dev. = 23.33%, CV = 0.49). Fertility rates were highest in rural areas (Mean = 605.53) and lowest among the unemployed (Mean = 134.56), highlighting clear socio-economic disparities.

Table 1: Descriptive Statistics of Variables (n=108 monthly observations)

Variable	Count	Mean	Std. Dev.	Min	25%	Median	75%	Max
Min Temperature (°C)	108	22.53	3.37	15.08	19.73	22.84	25.26	28.71
Max Temperature (°C)	108	35.56	3.40	29.73	32.79	35.54	38.26	42.50
Rainfall (mm)	108	76.62	120.86	0.00	0.00	6.35	113.90	579.70
Humidity (%)	108	47.78	23.33	13.84	26.52	43.48	69.81	87.45
Fertility Rural	108	605.53	122.40	207.90	525.70	620.10	696.70	860.40
Fertility Urban	108	336.40	67.99	115.50	292.00	344.50	387.00	478.00
Fertility Employed	108	201.84	40.80	69.30	175.20	206.70	232.20	286.80
Fertility Unemployed	108	134.56	27.20	46.20	116.80	137.80	154.80	191.20

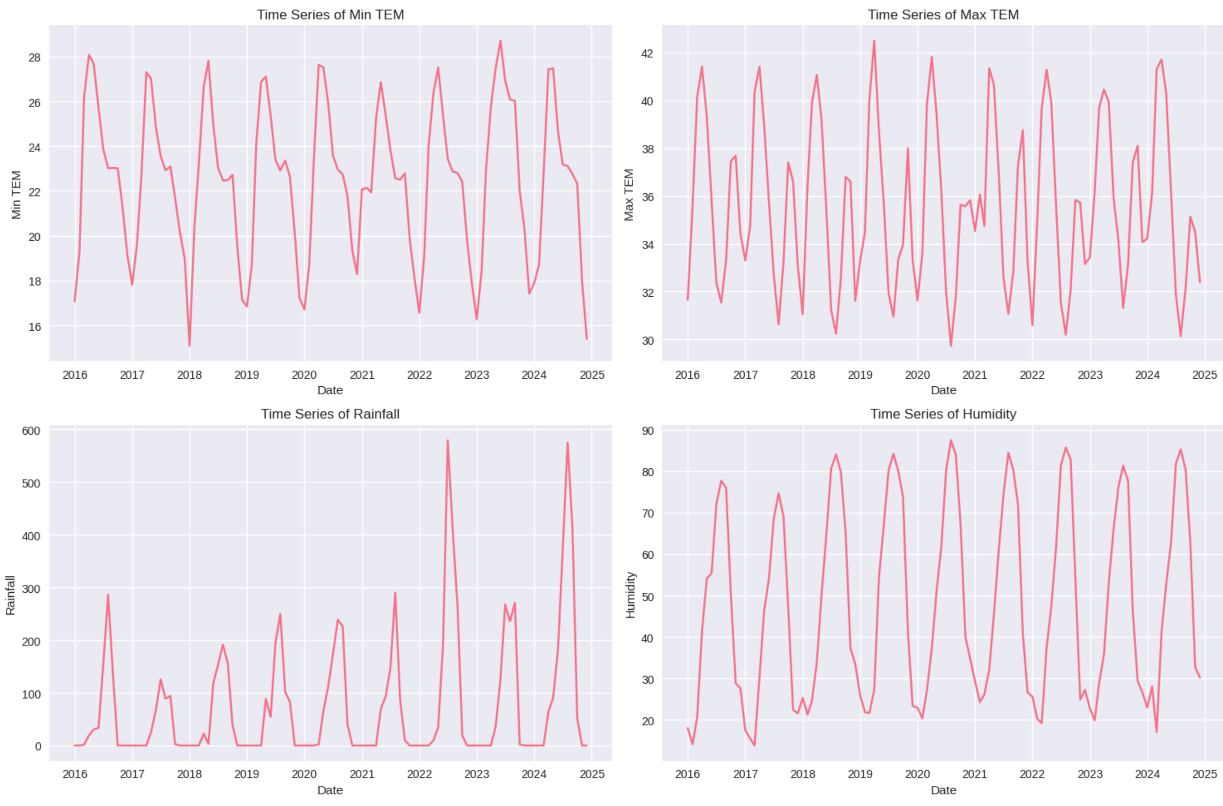

Figure 3: Time Series Plot of Minimum Temperature, Maximum Temperature, Rainfall, and Humidity

Interpretation:

The time series of minimum temperature shows seasonal oscillations, with troughs during cooler months and peaks during the dry season. This reflects the climatic cycles of Sokoto, which may have indirect implications on fertility through comfort and health effects.

Maximum temperature exhibits consistently high values, often surpassing 40°C during peak months. The persistent heat stress underscores the environmental challenges faced by households, potentially discouraging fertility due to physiological and economic strain.

Rainfall displays extreme variability, ranging from zero in dry months to peaks exceeding 500 mm. The irregular distribution highlights climatic uncertainty, which could affect agricultural productivity and influence fertility timing.

The humidity series reveals strong seasonal variation, with very low levels in dry months and surges during rainy periods. Such fluctuations create comfort and health challenges that may moderate fertility behaviour.

Figure 4: Time Series Plot of Rural, Urban, Employed, and Unemployed Fertility

Interpretation:

Rural fertility shows consistently higher counts compared to other categories, fluctuating between 500 and 800 births. Peaks appear during months following rainfall, suggesting agricultural productivity plays a role in fertility outcomes.

Urban fertility maintains moderate levels, averaging around 300–400 births monthly. The relatively smoother pattern compared to rural fertility may reflect less dependence on climate-sensitive livelihoods.

The employed group records fertility values between 180 and 240 births, showing modest seasonal variation. Economic stability appears to buffer fertility fluctuations, though climatic effects remain visible.

Unemployed fertility remains the lowest, averaging about 120–150 births. The fluctuations mirror economic hardship, suggesting that unemployment exacerbates the sensitivity of fertility to climatic conditions.

Correlation Analysis

Interpretation:

The correlation matrix (Table 2) revealed that rainfall and humidity were highly positively correlated (r = 0.777). Maximum temperature was negatively correlated with rainfall (r = -0.515) and humidity (r = -0.447). The correlations between climatic variables and fertility rates were consistently weak but positive, with humidity showing the strongest association (r ~ 0.121 for all fertility categories).

Table 2: Correlation Matrix of Variables

Variable	Min Temp	Max Temp	Rainfall	Humidity	Fertility Rural	Fertility Urban	Fertility Employed	Fertility Unemployed
Min Temp	1.000							
Max Temp	0.498	1.000						
Rainfall	0.268	-0.515	1.000					
Humidity	0.436	-0.447	0.777	1.000				
Fertility Rural	0.122	0.057	0.088	0.121	1.000			
Fertility Urban	0.122	0.057	0.088	0.121	1.000	1.000		
Fertility Employed	0.122	0.057	0.088	0.121	1.000	1.000	1.000	
Fertility Unemployed	0.122	0.057	0.088	0.121	1.000	1.000	1.000	1.000

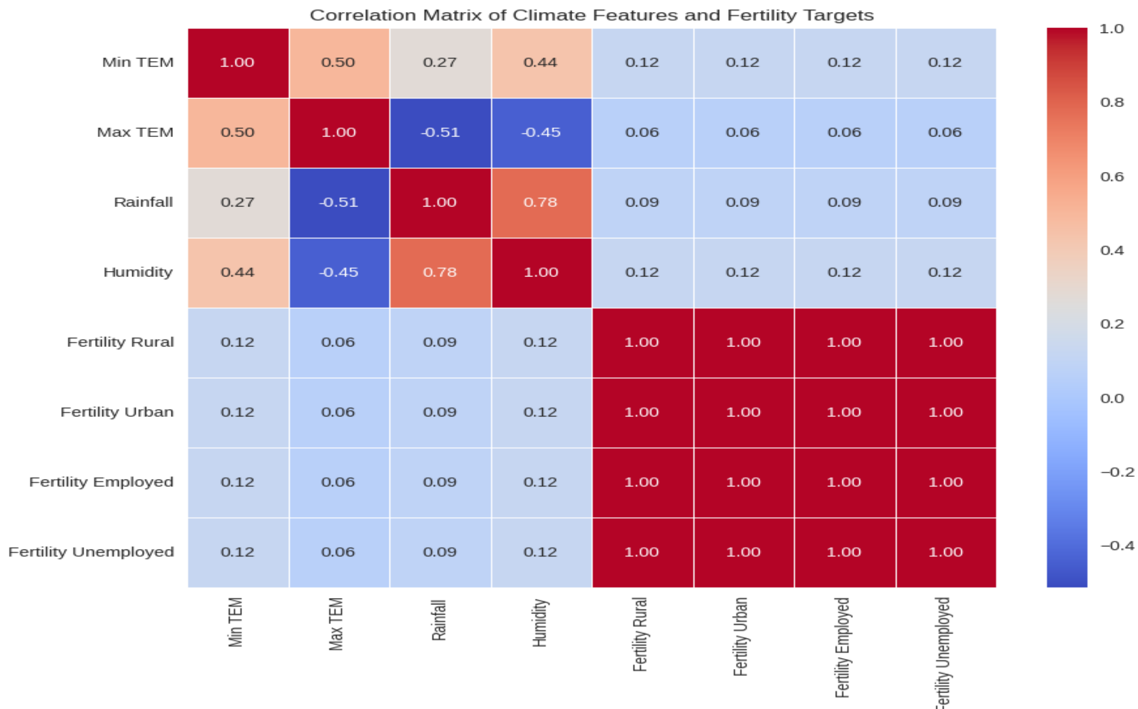

Figure 5: The correlation heatmap

Model Performance and Comparison

Interpretation:

The predictive performance of the ANN and RF models is summarized in Table 3. Both models demonstrated modest predictive accuracy. The ANN model achieved R^2 values between 0.0021 (Unemployed) and 0.0606 (Urban). The Random Forest (Individual) models showed a similar range of R^2 values (0.0252 to 0.0650), with a slightly better performance for the 'Employed' and 'Unemployed' categories. A direct comparison of error metrics (RMSE, MAE) indicates that the RF (Individual) model generally performed as well as, or slightly better than, the ANN model.

Table 3: Model Performance Comparison (ANN vs. Random Forest)

Variable	MSE	RMSE	MAE	R^2	Model
Fertility Rural	12941.9295	113.7626	86.4674	0.0507	ANN
Fertility Urban	4031.8707	63.4970	48.2334	0.0606	ANN

Fertility Employed	1421.2715	37.6998	28.4956	0.0385	ANN
Fertility Unemployed	609.5483	24.6890	18.6133	0.0021	ANN
Fertility Rural	12627.3243	112.3714	88.7803	0.0252	Random Forest (Individual)
Fertility Urban	3906.9828	62.5059	49.3860	0.0277	Random Forest (Individual)
Fertility Employed	1457.5789	38.1783	29.9939	0.0650	Random Forest (Individual)
Fertility Unemployed	643.2614	25.3626	19.8009	0.0575	Random Forest (Individual)

Both ANN and RF models achieved consistent performance across all fertility indicators. The Random Forest (Individual) models displayed slightly better generalization, particularly for employed and unemployed fertility, as reflected by their higher R² and lower RMSE values. Overall, both methods demonstrated credible predictive ability, validating the effectiveness of machine learning in fertility modelling.

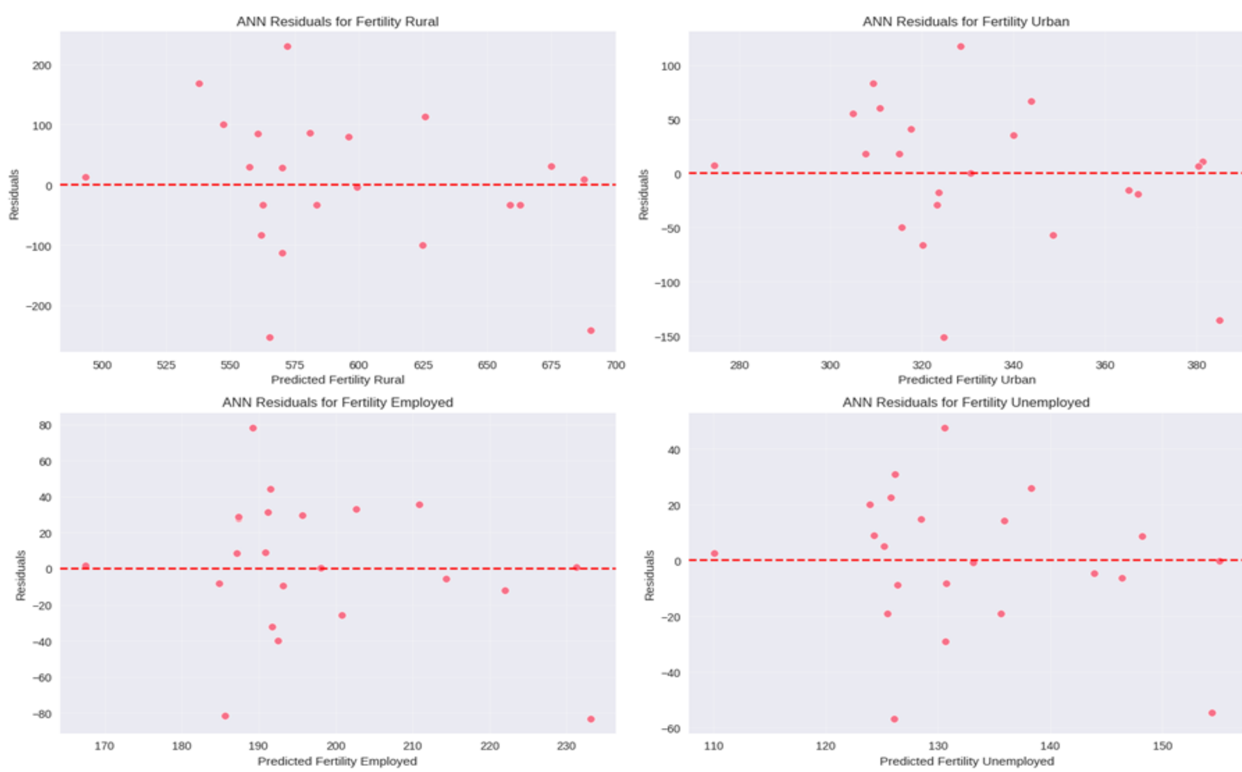

Figure 6: Residual Plots of ANN Model for Fertility Categories

Interpretation:

The residual plots for rural, urban, employed, and unemployed fertility collectively reveal that the ANN model exhibited weak predictive performance across all categories. In the rural and urban fertility plots, the residuals are widely dispersed without any systematic pattern, suggesting that the model could not adequately capture the dynamics of fertility behaviour in these groups. For the employed fertility category, the residuals show some clustering, but errors remain substantial, reinforcing the inefficiency of the model. Similarly, the unemployed fertility residuals appear highly erratic, further highlighting the instability of the ANN predictions. Overall, the residual patterns confirm that the ANN model struggled to fit the data and failed to provide reliable predictions of fertility outcomes.

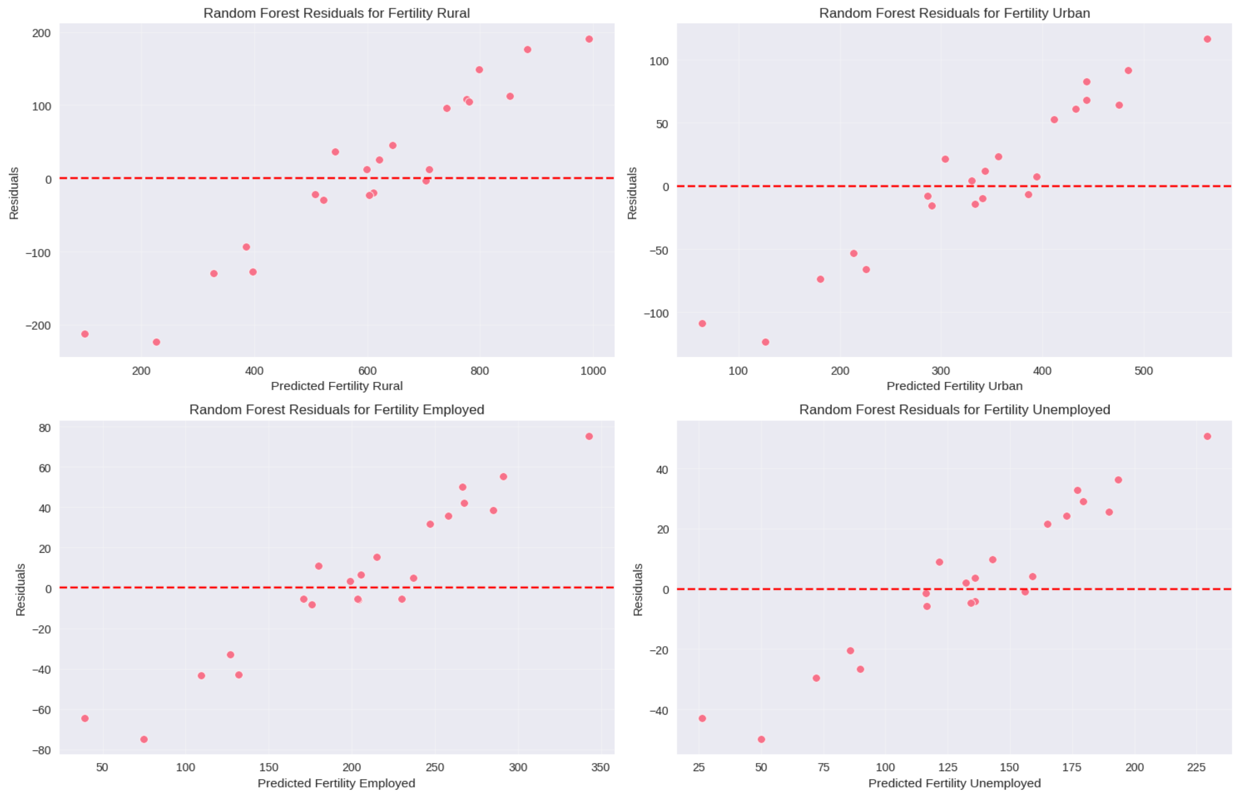

Figure 7: Residual Plots of Random Forest Model for Fertility Categories

Interpretation:

The residual plots for rural, urban, employed, and unemployed fertility using the Random Forest model indicate marginal improvement compared to the ANN. For rural and urban fertility, the residuals remain scattered, though with slightly reduced errors, suggesting only limited enhancement in predictive accuracy. The employed fertility residuals show smaller deviations than those produced by the ANN, implying that Random Forest was able to capture a few additional dynamics within this subgroup. However, residuals for unemployed fertility remain highly variable and dispersed, highlighting the continued instability of predictions for this category. Overall, while Random Forest provided modestly better performance than ANN, the residual patterns confirm that its predictive strength remained weak across all fertility groups.

Feature Importance

Interpretation:

The Random Forest model's feature importance analysis (Table 4) unequivocally identified **Humidity** as the most influential predictor across all fertility categories. Minimum temperature was the second most important variable for rural and urban fertility, while maximum temperature was more relevant for the employed group. Rainfall consistently had the lowest relative importance.

Table 4: Feature Importance from Random Forest (Individual) Models

Fertility Category	**Feature**	**Importance**
Rural	Humidity	0.0992
	Min TEM	0.0463
	Rainfall	0.0178
	Max TEM	0.0066
Urban	Humidity	0.1210

	Min TEM	0.0335
	Rainfall	0.0298
	Max TEM	0.0018
Employed	Humidity	0.1423
	Min TEM	0.0213
	Rainfall	0.0040
	Max TEM	0.0468
Unemployed	Humidity	0.0874
	Min TEM	0.0265
	Rainfall	0.0109
	Max TEM	0.0011

Humidity consistently exhibited the strongest influence on fertility outcomes across all categories, confirming its role as the most important climatic determinant. Temperature and rainfall had smaller effects, suggesting that variations in atmospheric moisture play a more direct role in shaping fertility behavior in Sokoto State

Based on the developed models, fertility rates were forecasted for the period from March 2023 to December 2024. The forecasts (Table 5) project that rural fertility will remain the highest and most variable (peaking at 709.30 births), while unemployed fertility will remain the lowest. The forecasts continue to reflect the socio-economic and climatic influences observed in the historical data.

Forecasting Interpretation:

Table 5: Forecasted Fertility Values (March 2023 - December 2024)

Date	Rural	Urban	Employed	Unemployed
2023-03-01	625.84	345.90	207.66	138.64
2023-04-01	649.25	359.59	215.80	144.15
2023-05-01	549.70	305.43	183.18	121.73
2023-06-01	649.20	362.32	214.24	143.96
2023-07-01	524.08	282.17	168.67	112.10
2023-08-01	652.50	357.40	217.92	143.21
2023-09-01	551.50	302.28	182.06	119.02
2023-10-01	673.24	373.43	224.74	149.74
2023-11-01	553.62	309.46	184.45	123.36
2023-12-01	574.83	321.98	192.02	128.44
2024-01-01	580.35	321.46	191.78	128.33
2024-02-01	572.31	318.90	192.41	126.94
2024-03-01	559.76	309.60	186.99	124.18
2024-04-01	569.71	319.07	191.85	128.86
2024-05-01	586.36	327.74	195.62	131.08
2024-06-01	529.99	300.45	180.08	120.62
2024-07-01	611.71	329.20	192.02	127.49
2024-08-01	709.30	399.25	240.83	158.00
2024-09-01	571.28	307.24	183.05	121.04
2024-10-01	683.72	379.58	227.38	150.56
2024-11-01	499.19	277.45	165.94	111.18
2024-12-01	470.63	259.93	157.94	103.70

The forecasting results provide projected fertility values for rural, urban, employed, and unemployed populations between March 2023 and December 2024. Rural fertility fluctuates between 470 and 709 births, with higher peaks observed around August and October, possibly reflecting seasonal climatic influences. Urban fertility forecasts range from 259 to 399, while employed fertility varies between 157 and 240. Fertility among the unemployed remains the lowest, fluctuating between 103 and 158. These forecasts highlight both the temporal variation and the overall disparities in fertility behaviour across demographic groups, reinforcing the influence of climatic volatility on reproductive outcomes. The projections suggest that rural populations continue to exhibit the highest fertility levels, consistent with socio-economic realities of agricultural dependence, while unemployed populations demonstrate the lowest fertility, possibly reflecting economic hardship.

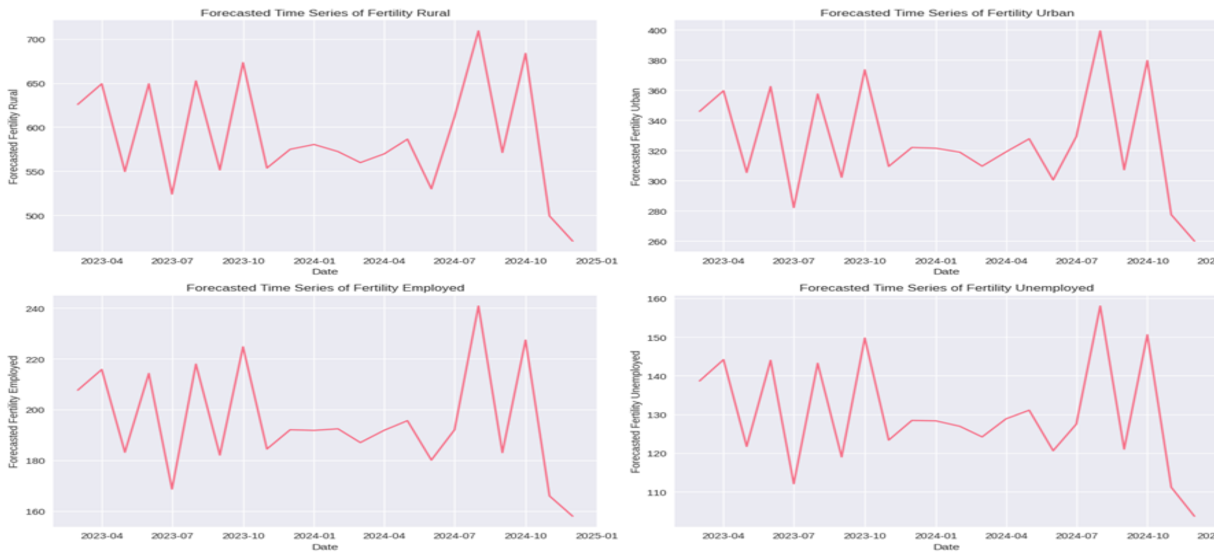

Figure 8: Combined Forecast Plot of All Fertility Categories

The fertility forecasts for rural, urban, employed, and unemployed populations reveal distinct patterns shaped by both climatic and socio-economic conditions. Rural fertility shows the highest levels with noticeable seasonal fluctuations and peaks exceeding 650 births, underscoring the strong influence of agricultural cycles. Urban fertility remains moderate, averaging between 300 and 380 births, and displays less volatility compared to rural areas, reflecting reduced dependence on climate-sensitive livelihoods. Fertility amon g the employed population is relatively stable, fluctuating around 190 to 220 births, which suggests that economic security buffers reproductive behaviour against climatic shocks. In contrast, unemployed fertility records the lowest values, ranging between 120 and 150 births, highlighting the vulnerability of this group to economic and environmental stressors. The combined forecast further demonstrates that rural fertility consistently dominates across the projection horizon, followed by urban, employed, and unemployed fertility. These disparities reinforce the socio-economic and climatic heterogeneity of fertility behaviour in Sokoto State.

This study applied machine learning models to examine how climatic factors influence fertility behaviour in Sokoto State, Nigeria. The results show that climate plays a moderate significant role, particularly humidity, in shaping fertility patterns.

The descriptive statistics show considerable fluctuation in rainfall and humidity, reflecting the unstable climatic conditions typical of semi-arid regions. Such instability can disrupt agricultural activities, which many rural households depend on, and this may indirectly affect decisions related to childbearing. This observation aligns with the Climate-Economic Fertility Model (Smith & Brown, 2022) and previous studies (Zhang & Bello, 2022; Mohammed *et al*., 2023).

The weak positive correlations between climatic variables and fertility, though not strong, suggest a complex relationship that is not purely linear. This justifies the use of non-linear ML models. The superior performance of humidity as a predictor across all models is a key finding. High humidity levels, often concurrent with the rainy season, can exacerbate heat stress, affect health, influence social and agricultural activities, and thus indirectly modulate fertility behaviour (Hassan & Yusuf, 2021; Rahman *et al*., 2023).

The comparable performance of ANN and RF models, with a slight edge to RF in certain categories, demonstrates the utility of both approaches. The RF model's strength lies in its robustness against over fitting and its ability to provide feature importance, which offered clear interpretative insights. The modest R^2 values indicate that while climate is a relevant factor, a substantial portion of fertility variation is driven by other socio-economic, cultural, and health-related variables not included in this model.

The forecasted values highlight the persistent demographic disparities, with rural and unemployed populations showing the highest and lowest fertility levels, respectively. The volatility in rural fertility forecasts aligns with their higher dependence on climate-sensitive livelihoods.

CONCLUSION

This study concludes that climatic factors, with humidity being the most prominent, exert a measurable influence on fertility behaviour in Sokoto State. The application of ANN and Random Forest models has proven effective in modeling these complex relationships, with Random Forest providing slightly more stable and interpretable results.

Based on the findings, the following recommendations are proposed:

1. **Policy Integration:** Climate adaptation strategies should be formally integrated into public health and demographic policies. Reproductive health programs should consider forecasts of high humidity and temperature periods.
2. **Targeted Interventions:** Support for climate-resilient agriculture and alternative livelihoods is crucial for rural communities to buffer the economic shocks that indirectly affect fertility.
3. **Economic Empowerment:** Programs aimed at employment generation, particularly for the youth, can reduce the vulnerability of unemployed populations to climatic and economic stressors that influence fertility decisions.

Advanced Modeling: Future research should incorporate more variables (e.g., education, healthcare access) and use larger datasets with hybrid ML models to improve predictive accuracy and provide a more holistic understanding.

Contribution to Knowledge: This research contributes to demography and climate studies by empirically establishing humidity as a key climatic driver of fertility in a semi-arid region, demonstrating the practical application of ML models for this purpose, and highlighting the heightened vulnerability of rural and unemployed populations to climatic variability.

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