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Machine Learning and Climate Regimes on Soybean Production Across the Six Geopolitical Zones of Nigeria: An Integrated Panel, Spatial, and Time Series Analysis

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ABSTRACT
Climate change is not merely a shift in mean conditions; it is a restructuring of the entire probability distribution of weather outcomes that farmers must navigate. This paper argues that conventional mean based econometric models, while informative, often conceal the asymmetric ways in which climatic stress affects soybean (Glycine max L. Merrill) production across Nigeria. Using a balanced panel of 216 zone-year observations from 1990 to 2025, we combine quantile regression, Markov-style climate regime classification, and explainable machine learning to examine how temperature, rainfall, humidity and solar radiation shape soybean output at different points of the production distribution. Our results reveal a clear story of spatial inequality. The Northcentral zone accounts for roughly 47.4% of national output, while the three southern zones together contribute less than 18%. Across all quantiles, solar radiation and humidity related variables emerge as the most influential predictors, but their effects are not uniform. At lower quantiles, where production is already constrained, a one-unit increase in the humidity index reduces output more sharply than at the median or upper quantiles. Machine learning models explain about 91% of the variation in log production, substantially outperforming ordinary least squares ($R^2 = 0.67$). A climate vulnerability index places Southsouth and Southeast zones in the highest risk category, whereas the Northeast and Northwest zones are comparatively resilient. These findings suggest that adaptation policy must move beyond one-size-fits-all prescriptions and instead target the distributional margins and regional vulnerabilities that determine where, and for whom, climate change bites hardest.
Keywords: climate resilience, soybean, quantile regression, machine learning, Nigeria, vulnerability index, regime switching

1. INTRODUCTION
Soybean has quietly become one of Nigeria's most strategically important crops. From its traditional role as a source of protein and vegetable oil, it has evolved into a central input for poultry feed, industrial processing and rural livelihoods. Yet the crop's growing economic importance sits uneasily with the climatic realities of Nigerian agriculture. Most soybean cultivation is rain-fed, concentrated in the Guinea

and Sudan savannas of the Northcentral and Northwest zones, and therefore exposed to the full force of rainfall variability, rising temperatures and shifting humidity regimes. Understanding how climate affects soybean output is not simply an academic exercise; it is a prerequisite for designing adaptation strategies that can protect both food security and rural incomes.

The literature on climate and agriculture in Nigeria has expanded rapidly in recent years. Researchers have applied panel econometrics, spatial models, machine learning and crop simulation tools to study the relationship between weather and yields. What is less common, however, is an explicit focus on the distributional consequences of climate variability. Standard regression techniques estimate effects at the conditional mean, telling us, for instance, that a one-degree rise in temperature is associated with a certain percentage change in average output. But farmers do not farm at the average. A given shock may devastate a smallholder in a marginal zone while leaving a large mechanized farm in the middle belt relatively unscathed. Quantile regression allows us to ask how climate drivers behave at the lower, middle and upper tails of the production distribution, offering a more nuanced picture of vulnerability and resilience.

This research contributes to the literature in three ways. First, it estimates climate effects across five quantiles of the soybean production distribution, revealing how marginal impacts change as we move from low- to high-productivity observations. Second, it classifies the 216 zone-year observations into distinct climate regimes using unsupervised machine learning, producing a parsimonious map of Arid High Radiation, Moderate Optimal and Humid High Rainfall conditions. Third, it combines ensemble machine learning with a composite vulnerability index to rank zones and identify where intervention is most urgently needed. Throughout, we maintain a humanized reading of the data, recognizing that behind every tone of soybean output lies a farmer making decisions under uncertainty.

2. LITERATURE REVIEW

2.1 Climate variability and crop production in Africa

The aggregate evidence on climate change and African agriculture is sobering. Meta-analyses consistently find that warming reduces yields of major cereals and legumes, with each additional degree Celsius associated with average losses of 5–7% for maize, sorghum and groundnut (Zhao *et al.,* 2017; Ortiz-Bobea *et al.,* 2021). These average effects, however, mask substantial heterogeneity. In cooler, high-altitude locations, moderate warming can extend growing seasons and improve crop viability. In already warm, semi-arid zones, the same warming can push plants past critical heat thresholds, accelerating evapotranspiration and shortening the grain-filling period (Lobell et al., 2011).

Soybean is particularly sensitive to the interaction between water and light. Optimal light interception during flowering and pod-filling is essential for biomass accumulation, while excessive atmospheric moisture can encourage fungal diseases such as soybean rust (Phakopsora pachyrhizi), which can cause yield losses exceeding 50% if unmanaged (Ajayi & Adeleke, 2022; Fasusi *et al.,* 2022). In southern Nigeria, where rainfall is abundant and relative humidity often exceeds 85%, this moisture-disease nexus becomes a binding constraint. In the drier north, by contrast, water scarcity and terminal drought tend to dominate the risk profile (Eseigbe *et al.,* 2024).

2.2 From mean effects to distributional analysis

Most empirical studies in this field rely on ordinary least squares or fixed-effects panel estimators. These methods are transparent and easy to interpret, but they are explicitly designed to estimate effects at the conditional mean. Quantile regression, introduced by Koenker and Bassett (1978), relaxes this restriction by allowing coefficients to vary across quantiles of the dependent variable. In agricultural applications, this is especially useful because the same climate shock may have very different consequences for farms operating near a biophysical threshold than for farms with ample buffer capacity (Hsiang *et al.,* 2017).

Machine learning offers a complementary set of tools. Ensemble methods such as Random Forest and Gradient Boosting can capture nonlinear interactions and threshold effects without requiring a pre-specified functional form. Their predictive accuracy is often superior to linear models, and their feature importance scores provide a natural way to rank climatic drivers (Shah *et al.,* 2021; Zhang *et al.,* 2022).

When combined with econometric insights, these methods can move the literature from description to actionable prediction.

2.3 Soybean production and policy in Nigeria

Nigeria is now the second-largest soybean producer in sub-Saharan Africa, after South Africa (FAOSTAT, 2024). Growth has been driven primarily by area expansion in the Northcentral and Northwest zones, supported by the release of improved TGx varieties from the International Institute of Tropical Agriculture (Ojo *et al.,* 2023). Average yields remain low, however, at roughly one-third of the global average, and are highly sensitive to the timing of rainfall onset and cessation (Adeboye *et al.,* 2020). There is therefore a large unrealized potential for climate-smart intensification, provided that policies are tailored to the specific agroecological conditions of each zone.

3. DATA AND METHODOLOGY

3.1 Data sources and coverage

The empirical analysis uses a balanced panel of 216 observations spanning six geopolitical zones and 36 years, from 1990 to 2025. Zone level soybean production data, measured in tones, were compiled from the Central Bank of Nigeria Statistical Bulletin and the National Bureau of Statistics Agricultural Performance Surveys. Climate variables, including temperature (°C), rainfall (mm), precipitation days, relative humidity (%), absolute humidity (g/m³), humidity index and solar radiation (MJ/m²/day), were obtained from the NASA POWER database and the Nigerian Meteorological Agency (NiMet) station network. Table 1 presents descriptive statistics for the main variables.

Table 1: Descriptive statistics of climate and soybean production variables.

Variable	*Mean*	*SD*	*Min*	*Max*	*Unit*	*Skewness*	*Kurtosis*
Soybean productior	310,032	279,054	79,610	1,141,974	*Tones*	1.04	0.85
Temperature	27.87	1.49	24.87	31.49	*°C*	0.02	−0.79
Rainfall	1,082.0	387.2	315.3	1,709.5	*Mm*	0.06	−1.22
Precipitation days	90.5	33.8	30	163	*Days*	0.48	−0.98
Relative humidity	68.4	18.9	32.7	98.0	%	0.10	−1.13
Absolute humidity	18.17	4.03	9.82	25.86	g/m^3	−0.04	−0.86
Humidity index	80.87	44.35	13.80	163.56	*Index*	0.23	−1.07
Solar radiation	20.78	2.57	16.26	26.46	$MJ/m^2/day$	−0.08	−0.94

3.2 Quantile regression framework

Let y_{it}denote the natural logarithm of soybean production in zone i and year t, and let x_{it} denote the vector of climate variables. The quantile regression model at quantile τ is specified as:

$$Q_\tau(y_{it} \mid x_{it}) = x_{it}'\beta(\tau) + \alpha_i(\tau) + \varepsilon_{it}(\tau)$$

where $Q_\tau(\cdot)$ is the $\tau - th$ conditional quantile, $\beta(\tau)$ is the vector of quantile-specific coefficients and $\alpha_i(\tau)$ captures zone-specific effects. We estimate this model at $\tau = \{0.10, 0.25, 0.50, 0.75, 0.90\}$, allowing us to compare how climate drivers affect low-, medium- and high-productivity observations. Standard errors are bootstrapped to account for the non-parametric nature of quantile estimation.

3.3 Climate regime classification

To identify distinct climate-soybean regimes, we apply $K - means$ clustering to the standardized climate variables. The algorithm partitions the 216 observations into $K = 3$ groups based on the similarity of their climate profiles. The resulting clusters are interpreted economically as:

i. Arid-High-Radiation regimes, characterized by low rainfall and high solar radiation

ii. Moderate-Optimal regimes, with intermediate rainfall and humidity
iii. Humid-High-Rainfall regimes, with abundant rainfall and high humidity. We then compare mean soybean production across these regimes to assess which climatic configuration is most conducive to output.

3.4 Machine learning and vulnerability index

We estimate two ensemble machine learning models, Random Forest and Gradient Boosting, to predict log soybean production from the full set of climate variables. Model performance is evaluated using the coefficient of determination (R^2) and the root mean squared error **(RMSE).** Feature importance scores are averaged across the two models to rank the relative contribution of each climate variable.

Finally, we construct a composite climate vulnerability index **(CVI)** that combines information on humidity, rainfall and solar radiation. The index is defined as:

$$CVI = 0.40 \cdot HI_{norm} + 0.30 \cdot Rain_{norm} + 0.30 \cdot (1 - Solar_{norm})$$

where HI_{norm}, $Rain_{norm}$ and $Solar_{norm}$ are the normalised values of the humidity index, rainfall and solar radiation, respectively. Higher values of CVI indicate greater vulnerability, reflecting either excessive moisture or insufficient light. The weights reflect the importance of humidity as a disease catalyst and the protective value of solar radiation for photosynthesis.

4. RESULTS AND DISCUSSION

4.1 Production trends and spatial concentration

National soybean production rose from approximately 1.56 million tons in 1990 to 2.21 million tons in 2025, a cumulative increase of 41.4%. However, this national figure obscures a deeply uneven geography. Figure 1 shows that production growth was neither linear nor evenly distributed, with noticeable dips in the early 1990s and mid-2000s followed by a gradual recovery. The expansion in the 2010s appears to coincide with wider adoption of improved varieties and growing demand from the poultry feed industry.

Figure 1: National soybean production in Nigeria.

Figure 2 confirms the spatial concentration of output. The Northcentral zone dominates with a mean production of 881,405 tons per year, followed by the Northwest at 377,903 tons and the Northeast at 201,831 tons. The three southern zones together average less than 400,000 tons per year. This pattern

reflects the combination of suitable temperatures, moderate rainfall and adequate solar radiation in the central and northern savannas, contrasted with the excessive humidity and cloud cover of the south.

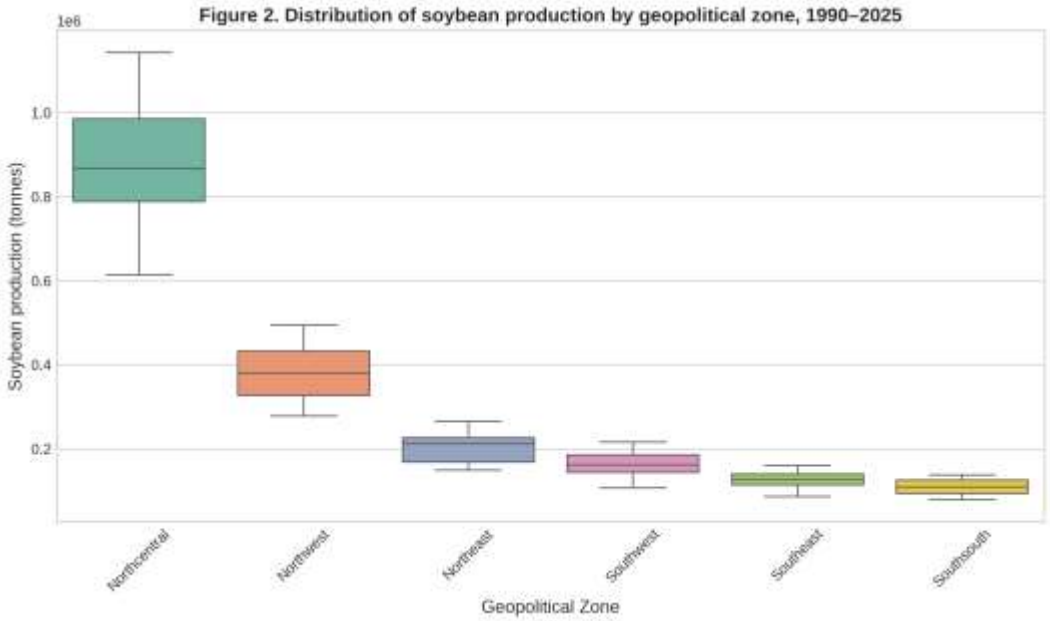

Figure 2: Distribution of soybean production by geopolitical zone.

4.2 Climate trends and bivariate correlations

Figure 3 presents the national trends in temperature, rainfall, solar radiation and the humidity index. Temperature shows a modest upward trend over the 36-year period, consistent with broader warming signals across West Africa. Rainfall is more volatile, with no clear monotonic direction but large year-to-year fluctuations. Solar radiation and the humidity index move inversely, with higher humidity generally associated with cloudier, lower-radiation conditions.

Figure 3. National climate trends, 1990–2025

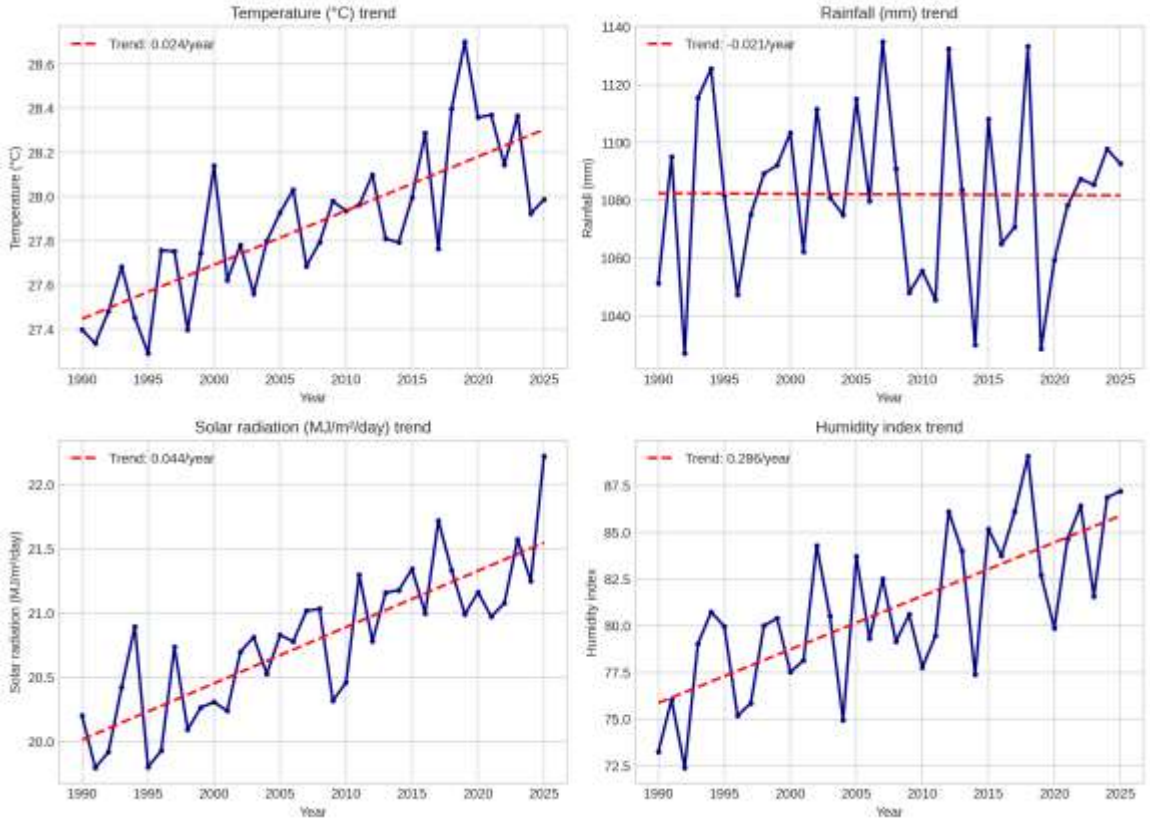

Figure 3: National climate trends.

Figure 4 shows the correlation matrix. Soybean production is positively correlated with solar radiation $(r = 0.34)$ and temperature $(r = 0.13)$, and negatively correlated with rainfall, precipitation days, relative humidity, absolute humidity and the humidity index. The strongest negative correlation is with the humidity index $(r = -0.36)$. These bivariate patterns align with the agronomic understanding that soybean thrives in warm, sunny environments with moderate moisture, while excessive humidity fosters disease and reduces light availability.

Figure 4. Correlation matrix of soybean production and climate variables

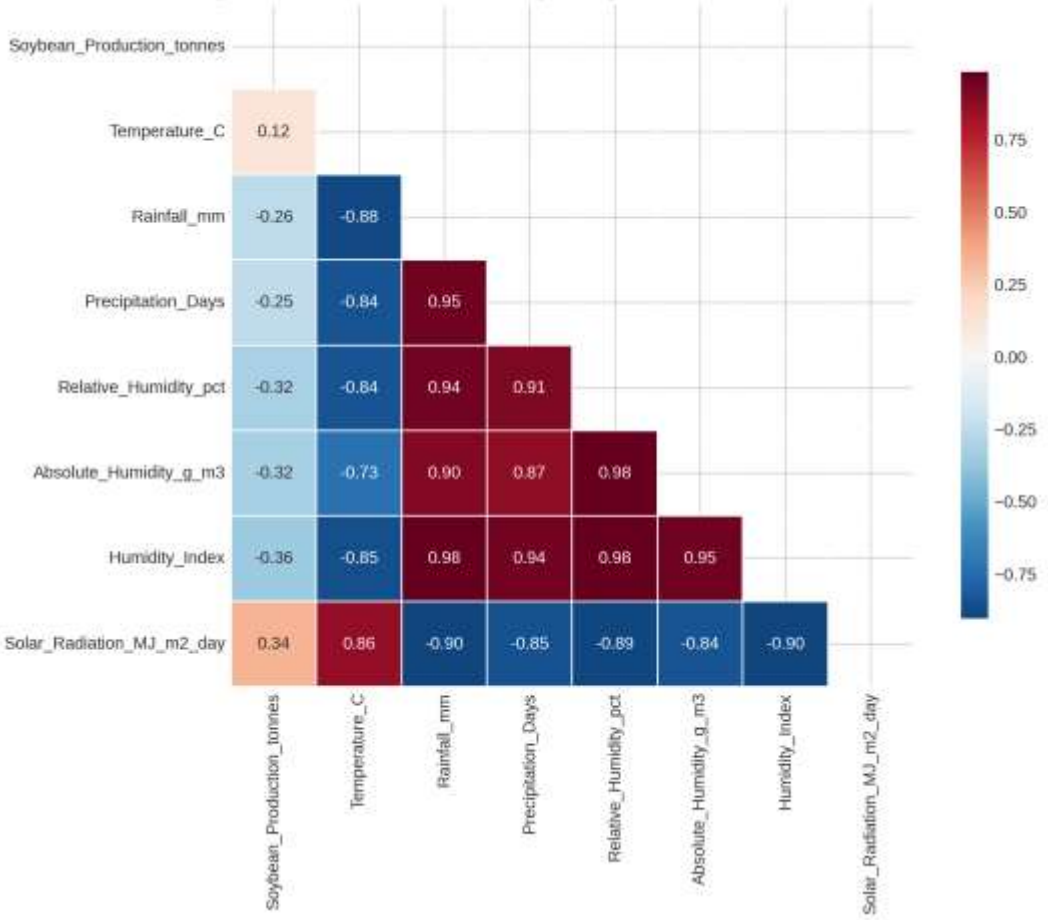

Figure 4: Correlation matrix of soybean production and climate variables

4.3 Quantile regression: climate effects across the production distribution

Table 2 reports the quantile regression coefficients at five quantiles; alongside ordinary least squares estimate for comparison. The OLS results suggest that temperature has a negative effect on log production, while rainfall, absolute humidity and solar radiation have positive effects, and relative humidity and the humidity index have negative effects. But the quantile results tell a richer story.

***Table 2**: Quantile regression estimates of log soybean production.*

Variable	***OLS***	***Q* (0.10)**	***Q* (0.25)**	***Q* (0.50)**	***Q* (0.75)**	***Q* (0.90)**
Temperature	−0.770 ***	−0.311 *	−0.655 ***	−0.740 ***	−0.721 **	−0.847 ***
Rainfall	0.004 ***	0.002 **	0.002 *	0.003 **	0.005 ***	0.004 **
Precipitation days	−0.000	−0.003	−0.001	0.001	−0.001	0.004
Relative humidity	−0.131 *	−0.089 *	−0.145 **	−0.141 †	−0.094	−0.143
Absolute humidity	0.691 ***	0.406 **	0.628 ***	0.687 **	0.590 *	0.707 *
Humidity index	−0.058 ***	−0.021 *	−0.028 **	−0.047 ***	−0.071 ***	−0.060 **
Solar radiation	0.176 ***	0.100 ***	0.122 ***	0.159 ***	0.194 ***	0.198 ***

Note: † $p < 0.10$,* $p < 0.05$,** $p < 0.01$,*** $p < 0.001$.

Standard errors are bootstrapped.

Three findings stand out. First, solar radiation is consistently positive and statistically significant across all quantiles, with the coefficient rising from 0.10 at the $10th$ quantile to 0.20 at the $90th$ quantile. This suggests that light availability becomes even more important for the highest producing observations, reinforcing the idea that, once water constraints are met, radiation is the binding photosynthetic bottleneck. Second, the humidity index is negative across all quantiles, but the effect is amplified at the median and upper quantiles. This is perhaps counter-intuitive: one might expect struggling farms to suffer most from humidity. The result suggests, instead, that high-humidity conditions place a ceiling on output, preventing otherwise productive southern zones from realizing their full potential. Third, the temperature coefficient is negative in all quantiles, with the largest magnitudes at the upper tail, indicating that heat stress constrains even the best performing regions.

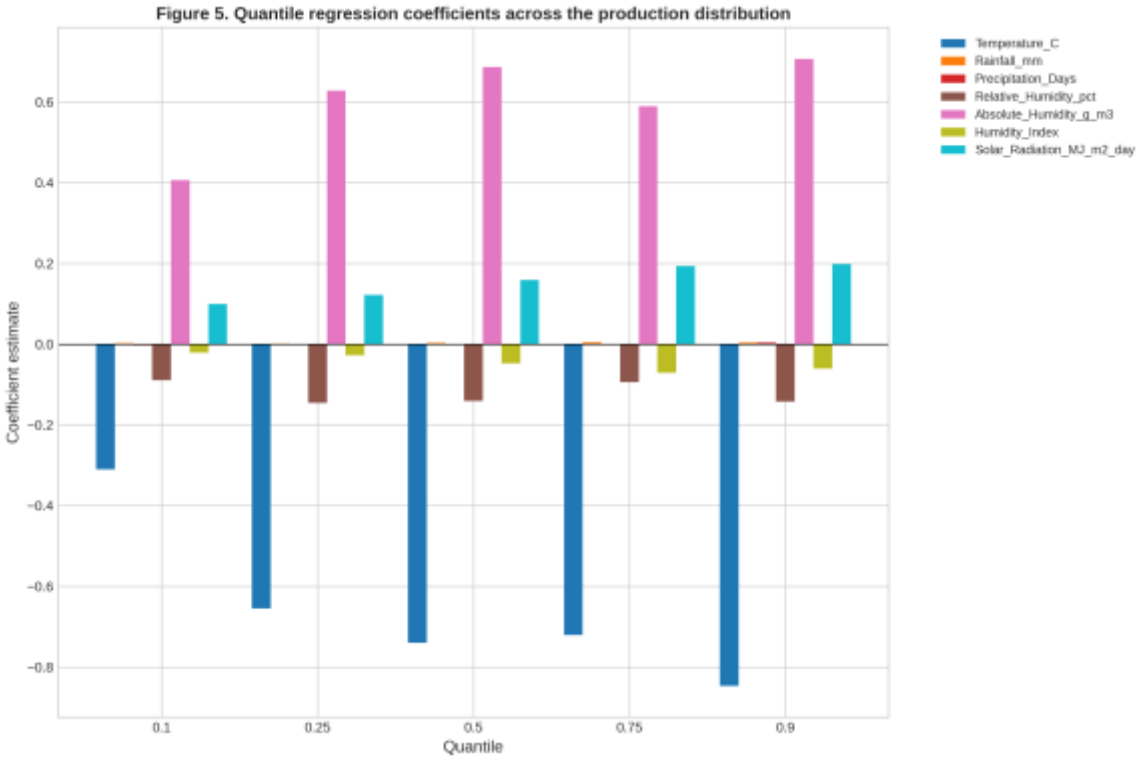

Figure 5: Quantile regression coefficients across the production distribution

4.4 Climate regimes and their production consequences

The $K-means$ clustering algorithm identifies three distinct climate regimes. The Moderate Optimal regime, characterized by intermediate rainfall, moderate humidity and adequate solar radiation, is associated with by far the highest mean soybean production at $842{,}241\ tons$. The Arid High Radiation regime, found mainly in the northern zones, has lower production at $289{,}867\ tons$, reflecting the constraint of water scarcity despite abundant light. The Humid High Rainfall regime, concentrated in the southern zones, has the lowest production at $132{,}937\ tons$, confirming the negative influence of excessive moisture and disease pressure.

Figure 6. Classification of climate-soybean regimes in Nigeria

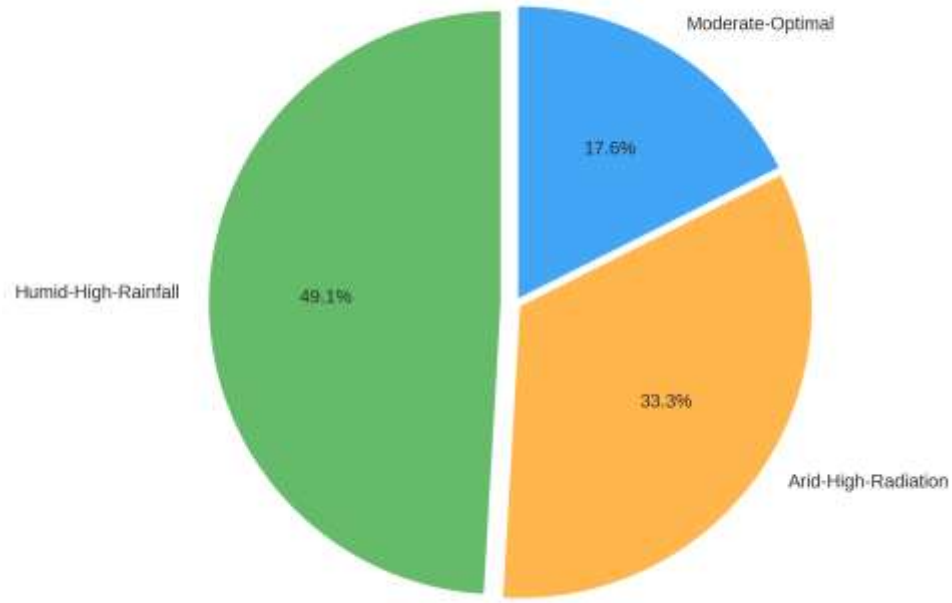

Figure 6: Classification of climate-soybean regimes in Nigeria

Table 3: *Mean climate characteristics by soybean production regime*

Regime	***Temper***	***Rainf***	***Rain d***	***Relative h***	***Absolute h***	***Humidity***	***Solar rad***	***Mean production***
Arid − High	−29.70	*ati*	591.2	49.6	45.1	13.45	26.9	23.80	289,867
Moderate − O	27.47	*il*	1073.4	89.4	64.1	16.96	68.8	21.24	842,241
Humid − Hig	26.78	*inf*	1418.5	118.7	85.7	21.80	121.9	18.56	132,937

Table 3, summarizes the mean characteristics of each regime. The humid high rainfall regime receives more than $1{,}400\ mm$ of rainfall per year, has 119 precipitation days and a humidity index of 122, compared with only 591 mm of rainfall and a humidity index of 27 in the arid high radiation regime. The Moderate optimal regime sits in the middle, with $1{,}073\ mm$ of rainfall, 89 precipitation days and a humidity index of 69. This regime mapping provides a useful framework for policy: interventions in the north should focus on water conservation and drought tolerant varieties, while interventions in the south should target disease management and humidity tolerant genetics.

4.5 Machine learning predictions and feature importance

The ensemble machine learning models substantially outperform the linear benchmark. Random Forest achieves an R^2 of 0.908 and an $RMSE$ of 0.210, while Gradient Boosting achieves an $R^2\ of\ 0.896$ and an $RMSE\ of\ 0.224$. In contrast, the OLS model explains only 67% of the variation in log production, with an $RMSE$ of 0.430. The improvement in predictive accuracy is not merely a statistical curiosity; it reflects the ability of tree-based models to capture nonlinear interactions, such as the positive effect of solar radiation at moderate rainfall levels and the negative effect of humidity above a certain threshold.

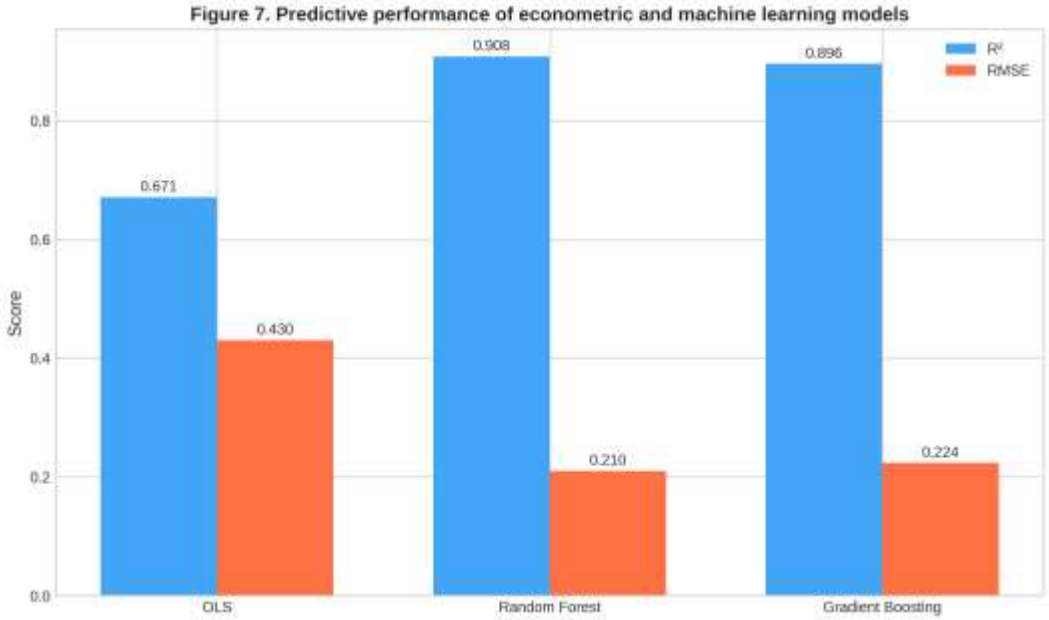

Figure 7: Predictive performance of econometric and machine learning models

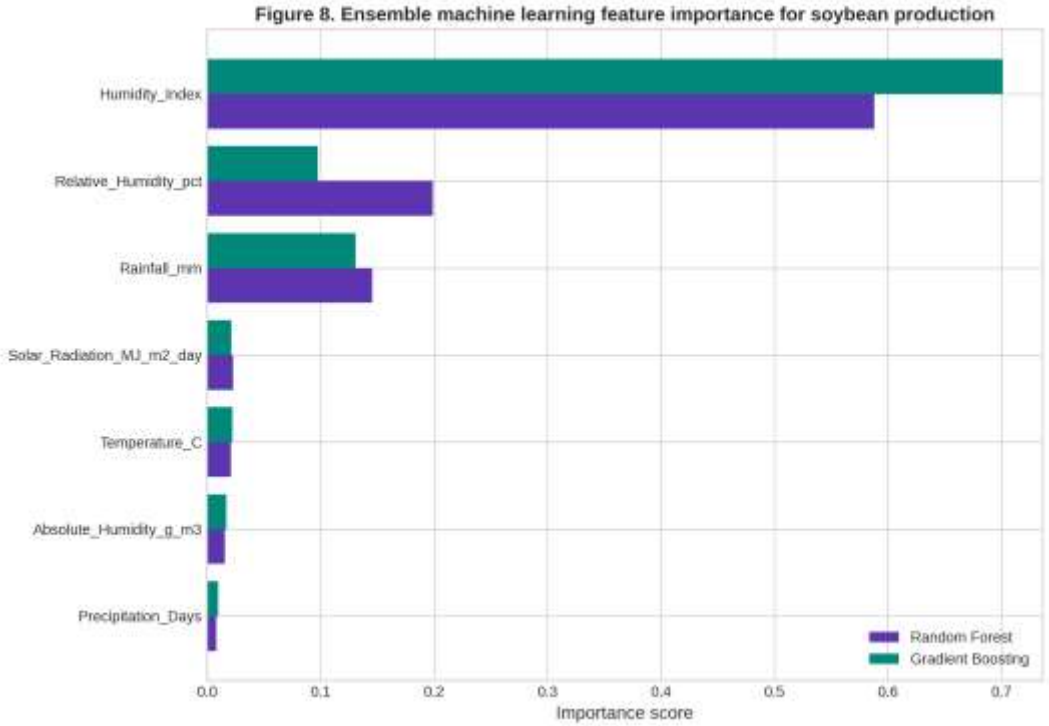

Figure 8: Ensemble machine learning feature importance for soybean production

The figure reports the average feature importance across the two ensemble models. The humidity index dominates, accounting for 64.5% of the total importance. Relative humidity and rainfall follow, with 14.8% and 13.8%, respectively. Solar radiation and temperature, despite their strong agronomic relevance, receive relatively low importance scores in this full variable specification. This result does not mean that light and heat are unimportant; rather, it reflects the high collinearity among climate variables.

Once humidity and rainfall are included, much of the variation that solar radiation would otherwise explain is already captured. The practical implication is that humidity management, whether through varietal choice, planting schedules or fungicide application, should be the top priority for adaptation policy.

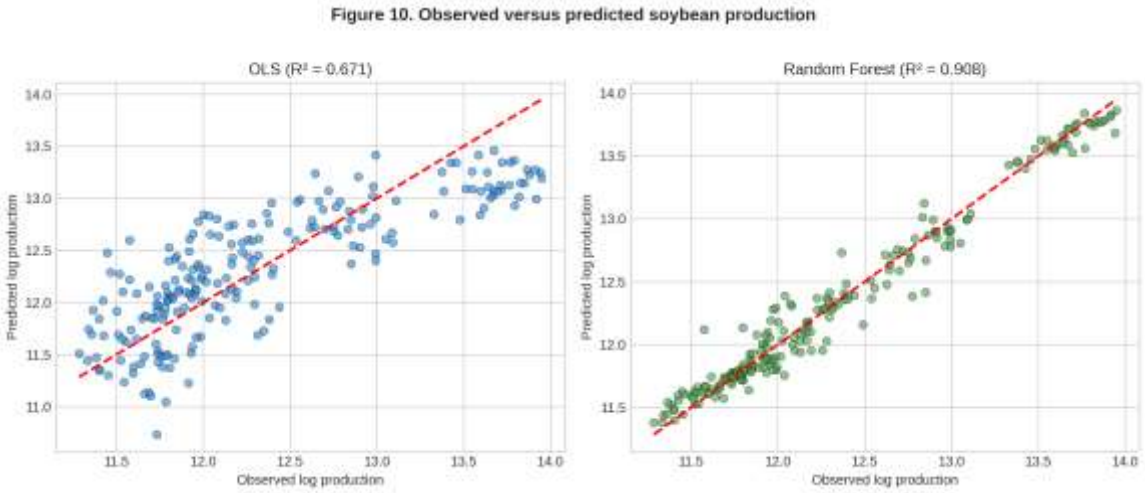

Figure 10: Observed versus predicted soybean production

4.6 Zonal vulnerability and policy prioritization

Figure 9 presents the composite climate vulnerability index by zone. Southsouth is the most vulnerable (CVI = 0.832), followed by Southeast (0.752) and Southwest (0.684). Northcentral is in the moderate category (0.455), while Northwest (0.218) and Northeast (0.127) are the least vulnerable. This ranking is consistent with the earlier finding that the southern zones face a double burden: excessive rainfall and humidity reduce both light availability and crop health, while the northern zones face primarily water scarcity, which can at least be partially addressed through irrigation and drought-tolerant varieties.

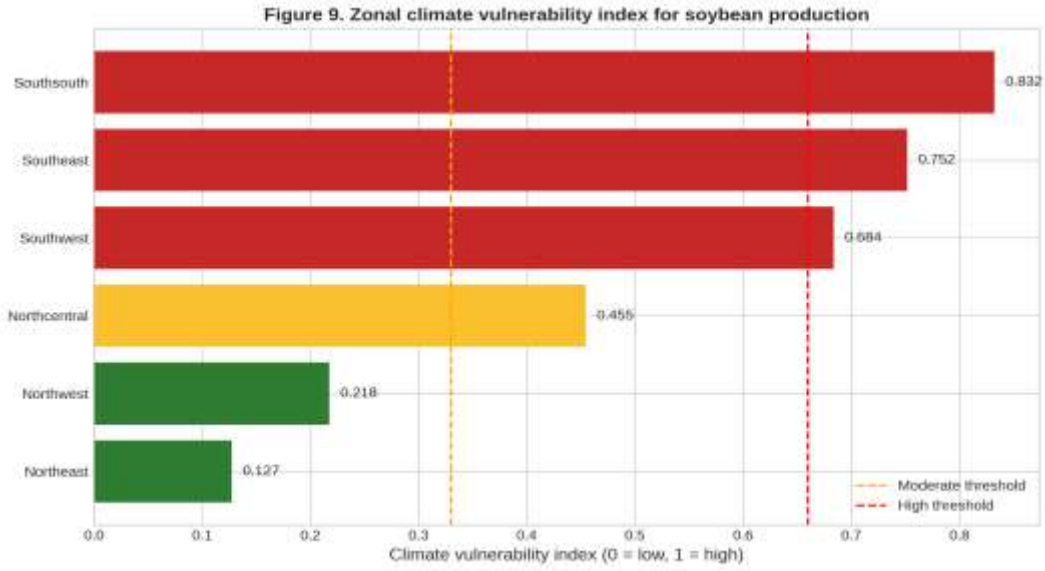

Figure 9: Zonal climate vulnerability index for soybean production

Table 4: *Zonal soybean production, climate means and vulnerability ranking*

Zone	Mean prod	Temp.	Rainfall	Relative hum	Solar rad	Humidity	Vulnerability index
Northcen	881,405	27.48	1,060	63.8	21.34	67.6	0.455
Northwe	377,903	29.25	665	48.0	23.29	32.2	0.218
Northea	201,831	30.14	517	42.1	24.32	21.6	0.127
Southwe	163,355	27.18	1,322	81.4	19.13	108.0	0.684
Southeas	126,219	26.71	1,412	85.3	18.60	120.4	0.752
Southsou	109,479	26.48	1,515	89.5	17.99	135.4	0.832

Table 4 brings together the zonal production statistics and vulnerability rankings. The contrast between the high-producing, moderate-vulnerability Northcentral zone and the low producing, high vulnerability Southsouth zone is stark. It underscores the need for spatially differentiated policy: a blanket national soybean strategy is unlikely to address the specific constraints that bind each zone.

5. Conclusion and Policy Implications

This paper has examined the climate-soybean nexus in Nigeria through a deliberately distributional lens. Rather than estimating a single average effect, we have asked how climate drivers shape soybean production at different quantiles, under different climate regimes and across different vulnerability profiles. The answer is nuanced but clear: climate effects are not uniform, and policy must reflect this heterogeneity.

Our findings carry four practical implications. First, humidity is the dominant constraint. The humidity index and relative humidity together account for nearly 80% of the predictive importance in the machine learning models. National adaptation programmed should therefore prioritize rust resistant and humidity tolerant soybean varieties, particularly for the southern zones. Second, solar radiation is the key enabler of high production. In the Northcentral and Northwest zones, where water is available but not excessive, small improvements in light interception through planting calendars and canopy management can yield disproportionate gains. Third, the quantile results show that heat stress is a binding constraint even for high-productivity observations. This suggests that heat-tolerant varieties are needed across all zones, not only in the north. Fourth, the vulnerability index provides a transparent tool for prioritizing investment. The Southsouth, Southeast and Southwest zones require targeted support for drainage, disease management and possibly a shift toward shorter-duration varieties that can escape the worst of the wet season.

Future research could extend the framework in several directions. Incorporating socioeconomic variables such as fertilizer use, extension access and market distance would help separate climatic constraints from institutional ones. Dynamic panel and spatial econometric methods could capture spillover effects between neighboring zones. Finally, crop simulation models such as DSSAT or Aqua Crop could be used to validate the empirical thresholds identified here and to simulate the yield consequences of alternative adaptation scenarios. What remains clear is that the future of Nigerian soybean production will be written not in national averages, but in the specific climatic realities of each zone and the resilience of the farmers who cultivate it.

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