

Maize Yield Prediction Using Interval-Valued Fuzzy Sets as a Tool for Attaining Food-Security in Kaduna State

*¹Isah Ahmed Ibrahim, ²Adamu Yusuf and ³Ahmad Muazu

¹Department of Mathematical Sciences, Kaduna State University, Kaduna State, Nigeria.

²Department of Crop Science, Kaduna State University, Kaduna State, Nigeria.

³Department of Microbiology, Kaduna State University Kaduna State, Nigeria.

*Corresponding authors' email: ahmed.isah@kasu.edu.ng

ABSTRACT

Crop yield prediction is one of the most important pillars that have the potential to increase productivity and improve food security. As Maize is the largest grain crop grown almost everywhere in Kaduna State, its accurate yield estimation using environmental data and growth data before harvest is critical for food security and agricultural policy development. In this paper, a Maize Yield Prediction model using Interval-Valued Fuzzy Sets (IVFS) is developed, which allows each factor to be represented by an interval membership value rather than a single crisp value, to predict maize yields in the northern, central and southern zones of Kaduna State. It is discovered that the southern zone has a very high yield potential with an estimated yield of 6.1-7.5 tons/ha, followed by the central zone with 5.2 - 6.6 tons/ha, then the northern zone having 4.3-5.8 tons/ha. It is shown that the northern zone is suitable for drought-tolerant maize varieties while the southern zone is the most ecologically suitable zone for maize production, thereby making it the best for large-scale maize commercialization among all the three zones. It is demonstrated that the state experienced a north-to-south increase in predicted maize interval, with the Northern Zone having the lowest predicted range and the Southern Zone having the highest. This pattern reflects differences in climate and other factors, including soil, fertilizer, hybrid seed, herbicide, and mechanization. The IVFS model effectively represents yield as an interval, capturing possible productivity ranges and supporting zone-specific agricultural planning and resource allocation.

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INTRODUCTION

Crop yield prediction has been identified as one of the important tools that have the potential to increase productivity and improve food security (Khaki and Wang 2019). Accurate crop yield prediction is useful in improving agricultural breeding, providing monitoring across diverse climatic condition and thus, protect against climatic challenges to crop production. It is as well crucial for agricultural planning, resource allocation, managing crop growth and achieving food security. The recent adverse effects of climate change on agricultural productivity have given rise to crop yield prediction which is essential in assisting farmers in anticipating the worst and preparing accordingly.

The main driving force of Kaduna State's economy is Agriculture with maize as the major crop, even though some other crops like groundnut, rice, soybean, sorghum and rice also contributes immensely to both food supply and income of the households aiding food security in the State.

However, maize yields swing in the State every year due to variability in rainfall, temperature, Soil properties, fertilizer application, modern tools and technology, and other meteorological factors which are extremely complex thereby affecting productivity of many farmers. For more details on these factors and maize yields see [Jagtab *et al.*, 1999; Ayinde *et al.*, 2011; Ammani, 2012; Suleiman *et al.*, 2019; Danladi *et al.*, 2021; NAERLS and FMARD, 2021; Tadama, 2024; Hiikyaa, 2024; Ahmad *et al.*, 2025; Abdullahi, *et al.*, 2025; StatsClimat., 2025; Ajeye *et al.*, 2025].

Maize being the main grain crop grown almost everywhere in Kaduna State, its accurate yield forecasting using

environmental and growth data before harvest is critical for food security and agricultural policy development. In other words, accurate maize yield prediction helps farmers and policy makers adjust the size of maize planting and maize production policies in a timely manner to cope with the constantly changing maize market (Kang *et al.*, 2020).

The ability to accurately predict maize crop yields has been a challenge over the years both globally and locally. Some scholars that used various models to predict maize yields include the following.

Chigwada *et al.* (2023) uses data analytics and machine learning to build a predictive model for estimating maize crop yield by Using historical maize crop yield, weather and environmental data, their Random Forest Regressor technique is trained to capture non-linear patterns and identify complex correlations in the data. Their model target both maize farmers and Policymakers.

Abdulbasit (2023) adopted an approach of modeling data of crop yield prediction from different areas of southern part of Nigeria and make predictions using three machine learning approaches of a decision tree classifier, random forest and support vector machine, and tested it using root mean square error to ensure the right prediction algorithm is adopted and the right values are obtained.

Zhang *et al.* (2023) develop a model of maize prediction based on a federated random forest algorithm using a real dataset obtained from maize field trials at 248 trial sites from the China National Crop Variety Tests from 2017 to 2021. Their approach enables breeding institutions to collaborate without disclosing or sharing their own data, and to jointly

model with tabular data including field breeding test phenotypes and environmental meteorology data stored locally by each participating institution. The method performed better and provides a cost-effective and efficient alternative for joint breeding for breeders and breeding teams. Wang et al. (2024) developed a yield prediction model based on a bipartite graph neural network to impute missing trait data and predict maize yield, where the maize planting data is initially converted to a bipartite graph data structure. When compared to other data imputation and prediction models, their method achieves even when missing data is not pre-processed.

However, these models only learn patterns from data and cannot adequately capture or communicate the level of uncertainty in input data (e.g., variable rainfall, inconsistent soil tests etc.); which is difficult to communicate confidence to policymakers.

A fuzzy set which is a class of elements with membership ratings was first introduced by (Zadeh, 1965). The theory serves as a tool used in tackling with uncertainties and other vague concepts. To develop this idea (Zadeh, 1975) extends it to interval-valued fuzzy set and further demonstrate its application. The reader may refer to [Zadeh, 1965; Zadeh, 1975; Gorzalczany, 1987; Yang et al., 2009; Isah, 2019; Isah, 2020] for more details on fuzzy structures and their applications.

This study develops an interval-valued fuzzy-set model for predicting maize-yield achievable based on the favourable level of climatic conditions, soil fertility and improved agricultural inputs across the three zones of Kaduna State. The IVFS model allows each factor to be represented by an interval membership value rather than a single crisp value, thus, capturing the level of uncertainty in input data, thereby improving prediction under uncertain environmental conditions. This will provide a more flexible and accurate way to handle these factors, consequently, enabling more robust yield predictions which is an important pillar for Attaining Food Security in the State.

Preliminaries

Definition 2.1 (Zadeh, 1965)

Let X be a non-empty universe set, then a fuzzy set A over X is defined as

$$A = \left\{ \left(x, \mu_A(x) \right) \mid x \in X \right\}, \quad \text{Where } \mu_A \text{ is a membership function? } \mu_A: X \rightarrow [0, 1].$$

Let A and B be two fuzzy sets over a set X , then

$$(i) A \subseteq B \text{ iff } \mu_A(x) \leq \mu_B(x), \quad \forall x \in X.$$

$$(ii) A \cup B = \max\{\mu_A(x), \mu_B(x)\}, \quad \forall x \in X.$$

$$(iii) A \cap B = \min\{\mu_A(x), \mu_B(x)\}, \quad \forall x \in X.$$

$$(iii) A - B = \min\{\mu_A(x), 1 - \mu_B(x)\}, \quad \forall x \in X.$$

$$(iv) \bar{A} = \{1 - \mu_A(x)\}, \quad \forall x \in X.$$

Definition 2.2 (Zadeh, 1975)

An interval-valued fuzzy set $\hat{X}$ on an universe U is a mapping such that $\hat{X}: U \rightarrow \text{Int}([0,1])$ where $\text{Int}([0,1])$ stands for the set of all closed subintervals of $[0,1]$, the set of all interval-valued fuzzy sets on U is denoted by $\tilde{P}(U)$.

Suppose that $\hat{X} \in \tilde{P}(U), \forall x \in U, \mu_{\hat{X}}(x) = [\mu_{\hat{X}}^-(x), \mu_{\hat{X}}^+(x)]$ is called the degree of membership an element x to $\hat{X}$. $\mu_{\hat{X}}^-(x)$ and $\mu_{\hat{X}}^+(x)$ are referred to as the lower and upper degrees of membership x to $\hat{X}$ where $0 \leq \mu_{\hat{X}}^-(x) \leq \mu_{\hat{X}}^+(x) \leq 1$.

Definition 2.3 (Gorzalczany 1987)

The complement, intersection and union of the interval-valued fuzzy sets are defined as follows: let $\hat{X}, \hat{Y} \in \tilde{P}(U)$, then

The complement of $\hat{X}$ is denoted $\hat{X}^c$ where

$$\mu_{\hat{X}^c} = 1 - \mu_{\hat{X}}(x) = [1 - \mu_{\hat{X}}^+(x), 1 - \mu_{\hat{X}}^-(x)];$$

The intersection of $\hat{X}$ and $\hat{Y}$ is denoted by $\hat{X} \cap \hat{Y}$ where

$$\mu_{\hat{X} \cap \hat{Y}}(x) = \inf[\mu_{\hat{X}}(x), \mu_{\hat{Y}}(x)] = [\inf(\mu_{\hat{X}}^-(x), \mu_{\hat{Y}}^-(x)), \inf(\mu_{\hat{X}}^+(x), \mu_{\hat{Y}}^+(x))];$$

The union of $\hat{X}$ and $\hat{Y}$ is denoted by $\hat{X} \cup \hat{Y}$ where

$$\mu_{\hat{X} \cup \hat{Y}}(x) = \sup[\mu_{\hat{X}}(x), \mu_{\hat{Y}}(x)] = [\sup(\mu_{\hat{X}}^-(x), \mu_{\hat{Y}}^-(x)), \sup(\mu_{\hat{X}}^+(x), \mu_{\hat{Y}}^+(x))].$$

MATERIALS AND METHODS

The study area is Kaduna State of Nigeria which lies within Longitude: 7.4° E and Latitude: 10.5° N. It covers the 23 Local Government Areas of the State and in this research, we followed their categorization as Northern zone comprising Zaria, Sabon Gari, Soba, Ikara, Kubau, Makarfi, Kudan and Lere Local Governments Areas, Central zone comprising Kaduna North, Kaduna South, Chikun, Igabi, Giwa, Kajuru and Birnin Gwari Local Government Areas, and the Southern zone comprising Jema'a, Kaura, Sanga, Kachia, Zangon Katak, Jaba, Kauru and Kagarko Local Government Areas. The categorization was considered as the zones slightly differ in climate, soils and topography, all of which influence maize productivity. This classification enables the Interval Value Fuzzy Set (IVFS) prediction model to account for these spatial differences and produce more realistic yield estimates.

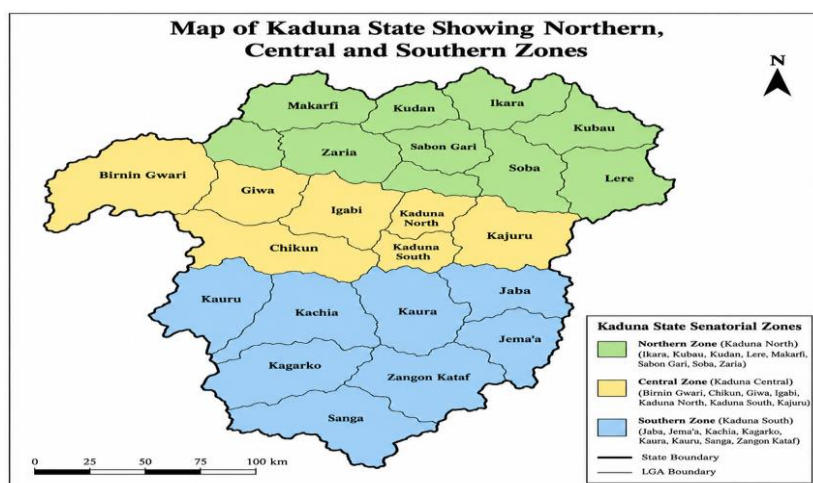


Figure 1: Map of Kaduna State Showing the Northern, Central and Southern Study Zones. Source: Adapted from Kaduna State Government (2026).

Development of the Interval Value Fuzzy Sets (IVFS) Maize Yield Prediction Model

Historical climatic conditions in Kaduna State vary considerably across the Northern, Central and Southern zones. Studies by Abaje and Oladipo (2019), who uses temperature and rainfall records from 1971–2016 at Kafanchan, Kaduna and Zaria, representing the southern, central and northern parts of the State respectively, Goma (2024) who used climate data from 12 NASA archive stations for 1984–2021 and Aganbi et al. (2021) that examined rainfall and temperature variability in relation to maize production in Kaduna State for 1999–2016 using climate data obtained from the Nigerian Meteorological Agency (NiMet); reported significant variations and changes in rainfall and temperature across Kaduna State and their relevance to maize production. Rainfall ranges from about 1,000 mm in the north around Zaria and below in the far north to approximately 1,700 mm in the south around Kafanchan, with Central Kaduna having an intermediate pattern. These climatic variations provide an empirical basis for distinguishing the three zones and defining the temperature and rainfall intervals used as inputs in the interval-valued fuzzy model for maize-yield prediction.

The soil intervals used in the interval-valued fuzzy model were based on the dominant soil textural characteristics reported in historical soil surveys and soil-characterization studies within Kaduna State by Federal Department of Agricultural Land Resources (FDALR), Soil Survey Division (1990), Esu et al. (1985), Jimoh et al. (2018), Ibrahim et al. (2020), Atiyong and Michael (2022), Awwal (2023) and that of Garba et al. (2023) who study sampled agricultural soils in Giwa, Kubau, Jaba and Kachia, providing useful evidence across northern, central and southern parts of the State. Findings show that Northern Kaduna is generally characterized by sandy-loam to loamy soils, Central Kaduna by loamy-sand to sandy-loam/loam soils, while Southern Kaduna contains relatively more clay-loam to sandy-clay-loam soils. These intervals represent aggregated dominant soil-texture conditions within each zone and do not imply that every location within a zone has identical soil properties. On hybrid seed, fertilizer application, herbicide and mechanization, we consider the high interval criteria for all the zones for better yields as we aimed to forecast maize yield potential.

Our maize yield prediction model considers the following variables:

Table 1: Input Variables used in the IVFS Maize-Yield Prediction Model

Symbol	T	R	F	S	Hs	Hu	M	Y
Variable	Temperature	Rainfall	Fertilizer application	Soil suitability	Hybrid seed utilization	Herbicide usage	Mechanization	Predicted maize yield

We then aggregating these Variables into interval value fuzzy intervals based on observed intervals as:

Table 2: Linguistic Classes and Interval-Valued Fuzzy Memberships Input To Model Variables

Temperature	Linguistic Term	Interval (° C)	Membership Interval
	Low	20-24	[0.25, 0.45]
	Moderate	25-28	[0.46, 0.70]
	High	29-32	[0.71, 1.00]
Rainfall	Linguistic Term	Interval (mm)	Membership Interval
	Low	700 – 1000	[0.25, 0.50]
	Moderate	1001–1400	[0.51, 0.80]
Fertilizer Application	High	1401–1800	[0.81, 1.00]
	Linguistic Term	Interval (kg/ha)	Membership Interval
	Low	50–120	[0.20, 0.45]
	Moderate	121–180	[0.46, 0.70]
	High	181–300	[0.71, 1.00]
Soil Suitability	Soil Type		Membership Interval
	Sandy Loam		[0.50, 0.70]
	Loam		[0.72, 0.90]
	Loamy Sand		[0.55, 0.72]
	Clay Loam		[0.75, 0.92]
Hybrid Seed	Sandy Clay Loam		[0.70, 1.00]
	Level		Membership Interval
	High		[0.80, 1.00]
Herbicides	Level		Membership Interval
	High		[0.75, 0.95]
Mechanization	Level		Membership Interval
	High		[0.70, 0.98]

Aggregating Membership Values for the three zones based on the input variables of the zones we have:

Table 3: Aggregated IVFS Membership Intervals for the Three Kaduna State Zones

Variables	Ivfs membership intervals		
	Northern zone	Central zone	Southern zone
Temperature (T)	[0.60, 0.80]	[0.60, 0.70]	[0.44, 0.63]
Rainfall (R)	[0.40, 0.66]	[0.63, 0.76]	[0.90, 0.98]
Fertilizer (F)	[0.71, 0.80]	[0.71, 0.90]	[0.85, 0.98]
Soil (S)	[0.45, 0.58]	[0.65, 0.76]	[0.74, 0.97]
Hybrid Seed (Hs)	[0.75, 0.90]	[0.80, 0.90]	[0.85, 0.98]
Herbicides (Hu)	[0.55, 0.72]	[0.75, 0.95]	[0.85, 0.95]
Mechanization (M)	[0.70, 0.82]	[0.78, 0.96]	[0.86, 0.96]

Determination of Weights for the Input Variables

The relative importance of the input variables used in the interval-valued fuzzy set (IVFS) model was determined using the Analytic Hierarchy Process (AHP). The AHP was adopted to provide a systematic procedure for assigning weights to the climatic, soil and agricultural input variables used in the maize yield prediction model. The variables considered were rainfall, temperature, fertilizer, soil, hybrid seed, herbicide and mechanization.

A pairwise comparison matrix was constructed using the Saaty scale of relative importance. The comparison was based on the agronomic relevance of each variable to maize production in Kaduna State. In the comparison, rainfall was considered highly important because maize production in the study area is predominantly influenced by rainfall availability and distribution. Fertilizer was also assigned a high relative importance because adequate nutrient availability is essential

for maize growth and grain formation. Temperature was considered important because it influences germination, photosynthesis, crop development and maturity. Soil was assigned a lower weight than rainfall, fertilizer and temperature because its effects are associated with soil texture, fertility, nutrient availability and water-holding capacity.

Hybrid seed was assigned a moderate weight because improved hybrid varieties can provide higher yield potential under suitable growing conditions. Herbicide and mechanization received comparatively lower weights because their effects on yield are largely indirect. Herbicide contributes through effective weed control, while mechanization contributes mainly through improved timeliness and efficiency of farm operations. The resulting normalized AHP weights is presented as:

Table 4: Normalized AHP Weights of Model Input Variables

Variable	Temperature	Rainfall	Fertilizer	Soil	Hybrid Seed	Herbicides	Mechanization	Total
Weight	0.207	0.254	0.225	0.132	0.082	0.05	0.05	1.00

The results indicate that rainfall has the highest relative importance in the aggregation of the input variables, with a weight of 0.254, followed by fertilizer (0.225) and temperature (0.207). Soil has a weight of 0.132, while hybrid seed, herbicide and mechanization have weights of 0.082, 0.050 and 0.050, respectively.

It is important to note that these weights do not imply that rainfall contributes exactly 25.4% to maize yield or that fertilizer contributes exactly 22.5%. Rather, the weights represent the relative importance assigned to the variables when combining their normalized fuzzy values in the IVFS model.

The consistency of the pairwise comparison judgments was evaluated using the Consistency Ratio (CR). The calculated consistency ratio was approximately 0.0125 (1.25%), which is below the generally accepted threshold of 0.10 (10%). Therefore, the pairwise comparisons were considered acceptably consistent and the resulting weights were retained for the IVFS maize yield prediction model.

Thus, the weighted aggregation component of our interval value fuzzy sets (IVFS) maize yield prediction model is expressed as $Y = w_1T + w_2R + w_3F + w_4S + w_5Hs + w_6Hc + w_7M$, where Y represents maize yield prediction

index, w_i , variables' weights and T, R, F, S, Hs, Hu, M for the normalized interval-valued fuzzy memberships of temperature, rainfall, fertilizer, soil, hybrid seed, herbicide and mechanization, respectively.

The use of AHP therefore provides a transparent and mathematically consistent basis for assigning relative importance to the input variables before their aggregation within the interval.

Maize Yield Prediction Scale

The maize yield prediction scale was developed to provide a clear basis for interpreting the interval-valued fuzzy predictions generated by the proposed model. Since the IVFS model produces yield estimates as intervals rather than single-point values, it was necessary to establish yield classes that could be used to interpret the magnitude of the predicted maize yield.

The prediction scale ranges from $0 \leq Y \leq 1$ where Y represents *fuzzy maize yield prediction index*. Values closer to 0 indicate poor yield potential and values closer to 1 indicate excellent yield potential. The scale is presented as

Table 5: Fuzzy Yield-Index Classes and Corresponding Maize-Yield Ranges

Fuzzy interval Yield Index	Linguistic Interpretation	Estimated Yield
[0.00 – 0.20]	Very Low Yield	0 – 1.5 tons/ha
[0.21 – 0.40]	Low Yield	1.6 – 3.0 tons/ha
[0.41 – 0.60]	Moderate Yield	3.1 – 4.5 tons/ha
[0.61 – 0.80]	High Yield	4.6 – 6.5 tons/ha
[0.81 – 1.00]	Very High Yield	6.6 – 8.5 tons/ha

The prediction scale was divided into five categories: very low yield (0–1.5 tons/ha), low yield (1.6–3.0 tons/ha), moderate yield (3.1–4.5 tons/ha), high yield (4.6–6.5 tons/ha), and very high yield (6.6–8.5 tons/ha). The classification was designed to represent increasing levels of maize productivity within the range of yields considered for the Kaduna State study area. For example, the third category with 3.1–4.5 tons/ha, represents a moderate level of maize productivity. This range reflects production levels that are above very low and low productivity but remain relatively limited in comparison with the higher yield levels achievable under favourable climatic conditions, adequate soil fertility and improved agricultural inputs.

The boundaries of the classes were selected to provide distinct and practically interpretable groups for comparing the predicted yield intervals among the Northern, Central and Southern zones of Kaduna State. The scale also enables the predicted intervals to be interpreted consistently across the three zones.

It is to be noted that, the classification thresholds were established for this study based on the observed yield range and the need to provide meaningful categories for interpreting the model's interval predictions.

RESULTS AND DISCUSSION

Result

Northern Zone Maize Yield Prediction

Applying our interval value fuzzy model $Y = 0.207T + 0.254R + 0.225F + 0.132S + 0.082Hs + 0.05Hc + 0.05M$ to northern zone using the aggregated membership values for the zone in Table 3, we get $Y = [0.56895, 0.72536]$. Thus, the estimated yield according to our prediction scale, and based on the value of Y is 4.3 – 5.8 tons/ha indicating moderately high yield for the zone.

Central Zone Yield Prediction

Applying our interval value fuzzy model $Y = 0.207T + 0.254R + 0.225F + 0.132S + 0.082Hs + 0.05Hc + 0.05M$ to Central zone using the aggregated membership values for the zone in Table 3, we have $Y = [0.67187, 0.81006]$. Thus, the estimated yield is 5.2 – 6.6 tons/ha as per table 5. This indicates a high yield for the zone.

Southern Zone Yield Prediction

Applying our interval value fuzzy model $Y = 0.207T + 0.254R + 0.225F + 0.132S + 0.082Hs + 0.05Hc + 0.05M$ to Southern zone using the aggregated membership values for the zone in Table 3, we have $Y = [0.76381, 0.90373]$. This shows that the estimated yield for this zone is 6.1 – 7.5 tons/ha, signifying very high yield for the zone.

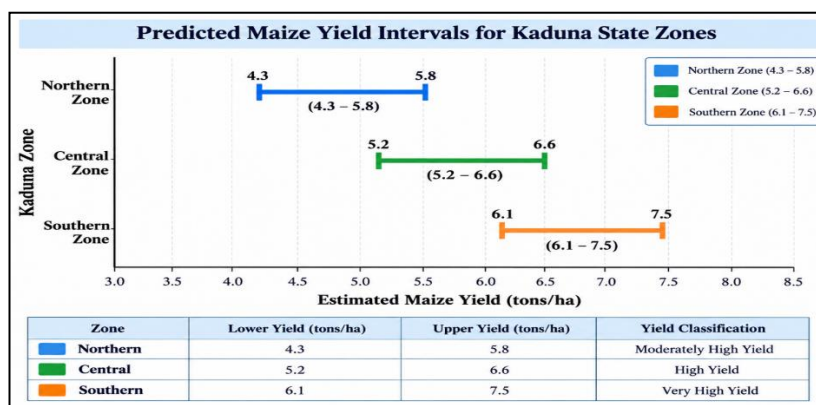


Figure 2: Predicted maize-yield intervals for the northern, central and southern zones of Kaduna State

Discussion

The results of the interval-valued fuzzy set model show differences in the predicted maize yield ranges across the Northern, Central and Southern Zones of Kaduna State. The Northern Zone recorded a predicted yield interval of 4.3–5.8 tons/ha, the Central Zone recorded 5.2–6.6 tons/ha, while the Southern Zone recorded 6.1–7.5 tons/ha. These differences indicate that the predicted maize productivity varies across the three zones, reflecting the differences in the climatic, soil and agricultural input conditions represented in the model.

The Northern Zone, with a predicted yield of 4.3–5.8 tons/ha, spans the moderate-to-high yield categories. The lower bound of 4.3 tons/ha falls within the moderate-yield category (3.1–4.5 tons/ha), while the upper bound of 5.8 tons/ha falls within the high-yield category (4.6–6.5 tons/ha). This indicates that maize production in the Northern Zone has the potential to move from moderate to high productivity depending on the prevailing combination of rainfall, temperature, soil conditions and agricultural inputs. The relatively lower predicted interval compared with the other zones may be

associated with the comparatively lower rainfall and higher temperatures characteristic of the northern part of Kaduna State. The zone is Suitable for drought-tolerant maize varieties.

The Central Zone produced a predicted yield interval of 5.2–6.6 tons/ha. This interval falls predominantly within the high-yield category, with its upper limit reaching the very-high-yield boundary of 6.6 tons/ha. This suggests favourable maize production conditions in the Central Zone. The combination of suitable climatic conditions, soil characteristics and agricultural inputs, particularly fertilizer, improved seed, herbicide and mechanization, contributes to the relatively high predicted productivity of the zone. The result also indicates that improvements in the management of these production factors could support movement toward the upper end of the predicted interval.

The Southern Zone recorded the highest predicted interval of 6.1–7.5 tons/ha, spanning the high-to-very-high yield categories. Both the lower and upper bounds indicate relatively high productive potential, while the upper bound of

7.5 tons/ha falls within the very-high-yield category (6.6–8.5 tons/ha). The higher predicted yield range in the Southern Zone may be associated with its generally higher rainfall and relatively lower temperatures compared with the Northern Zone, together with favourable soil and agricultural-input conditions. These conditions provide a potentially more favourable environment for maize growth and grain development. This is the best for large-scale maize commercialization among all the zones.

Thus, the results show a north-to-south increase in the predicted maize yield interval, with the Northern Zone having the lowest predicted range and the Southern Zone having the highest. This pattern is consistent with the climatic gradient across Kaduna State, particularly the generally increasing rainfall and decreasing temperature from north to south. However, the predicted differences should not be attributed to climate alone because the IVFS model incorporates several interacting variables, including fertilizer, soil, hybrid seed, herbicide and mechanization.

The findings demonstrate the usefulness of the IVFS approach in representing maize yield as an interval rather than as a single deterministic value. The intervals capture the possible range of productivity under the combined influence of the selected climatic, soil and agricultural input conditions. Consequently, the model provides a basis for identifying differences in production potential among the three zones and can support zone-specific agricultural planning and resource allocation.

CONCLUSION

The developed Interval-Valued Fuzzy Set (IVFS) model successfully predicts maize yield potential across the three agro-ecological zones of Kaduna State. We discovered that the Northern zone has a moderately high, central zone has high and Southern zone has very high maize yield potentials. It is discovered that climatic conditions, soil quality, fertilizer application, and agricultural inputs substantially influence maize productivity. Moreover, our approach of maize yield prediction provides a reliable framework for agricultural forecasting, food security planning, climate adaptation, and policy formulation in Kaduna State. We recommend that the government of Kaduna State should introduce Fertilizer and Input Subsidy Reform which will involve the Introduction of zonal-specific fertilizer policy, improve timely fertilizer distribution and support private-sector agro-input supply chains.

Mechanization should also be enhanced by establishing mechanization service centers, Subsidize tractor hiring services and encourage youth mechanized farming cooperatives.

The government should as well encourage agricultural data and decision systems by establishing GIS-based crop monitoring systems and Fuzzy logic decision-support systems. Digital agricultural databases and Real-time maize yield forecasting systems should also be established.

In addition to the above for the northern zone, the state government should introduce Climate-Smart Agricultural Policy by promoting drought-resistant maize varieties. Expand irrigation infrastructure and develop seasonal weather forecasting systems.

REFERENCES

Abaje, I. B., & Oladipo, E. O. (2019). *Recent changes in the temperature and rainfall conditions over Kaduna State, Nigeria*, Ghana Journal of Geography, 11 (2) 127–157. <https://doi.org/10.4314/gjg.v11i2>.

Abdullahi, I. M., Jatbong, J. N., Baraza, S. A. and Gazara, H. A. (2025). Adoption of Hybrid Maize Production Among Farmers In Sabon-Gari Local government Area, Kaduna State, Nigeria, Nigerian Journal of Agriculture and Agricultural Technology 5 (4A) 2811-1893.

Abdulbasit, A., Adewumi, S. E. and Yemi-Peters, V. (2023). Crop Yield Prediction in Nigeria Using Machine Learning Techniques: (A Case Study of Southern Part of Nigeria), UMYU Scientifica 2 (4) 31 – 38.

Aganbi, B., Ifeka, A., & Matini, J. L. (2021). *Assessment of rainfall and temperature variability on maize production in Kaduna State*, International Journal of Research Publications, 91 (1) 307–332. <https://doi.org/10.47119/IJRP1009111220212617>

Ahmad, M, Ahmed, A. M., Ariko, J. D. and Abdulkadir, H. (2025). Trends of Extreme Temperature and Rainfall Using Innovative Trend Analysis In Kaduna State, Nigeria, FUDMA Journal of Sciences (FJS) 9 (11) 407 – 420. DOI: <https://doi.org/10.33003/fjs-2025-0911-3983>

Ajeje, D. B., Dahiru, M. K., Ayiwulu, E. and Yusuf, G. (2025). Assessment of Physico Chemical Properties of Soils and Fertilizer Requirements in Southern Senatorial District in Kaduna State, Nigeria, British Journal of Environmental Sciences, 13 (3) 62-76.

Ammani, A. A., Ja'afaru, A. K., Aliyu, J. A. and Arab, A. I. (2012). Climate Change and Maize Production: Empirical Evidence from Kaduna State, Nigeria, Journal of Agricultural Extension 16 (1) 1-8. <http://dx.doi.org/10.4314/jae.v16i1.1>

Atiyong, B.R. and Michael, H.Y. (2022). Nature and Variation of Soil Properties under Different Land Management Practices in Southern Part of Kaduna, Kaduna State, Nigeria, Science World Journal 17 (1) 31-37.

Awwal Y.A. (2023). Influence of Topography on Pedologic Forms of Iron in Basement Complex Soils of Giwa Local Government Area, Kaduna State, Nigeria, Agro-Science Journal of Tropical Agriculture, Food, Environment and Extension 22 (3) 17 – 25.

Ayinde, T. B., Fola, A. J. and Ibrahim, U. (2011). Economic Advantage of Hybrid Maize over Open Pollinated Maize in Giwa Local Government Area of Kaduna State, American Journal of Experimental Agriculture 1 (3) 101-109.

Chigwada, T., Dzinomwa, M., Ndlovu, B., Sibanda, K. and Moyo, S. (2023). Maize Crop Yield Prediction Model Using Machine Learning, Proceedings of the 4th Asia Pacific Conference on Industrial Engineering and Operations Management Ho Chi Minh City, Vietnam, September 12-14, 106 – 113.

Danladi, E. B, Ntat, F. H. and Idakwo, D. A. (2021). Analysis of Factors Affecting Adoption of Premier Hybrid Seed Among Maize Farmers in Sabon-Gari Local Government Area of Kaduna State, Nigeria, FUDMA Journal of Agriculture and Agricultural Technology 7 (2) 67-75. doi: <https://doi.org/10.33003/jaat.2021.0702.049>

Esu, I. E., & Ojanuga, A. G. (1985). *Morphological, physical and chemical characteristics of Alfisol in the Kaduna area of*

Nigeria, Samaru Journal of Agricultural Research 3 (1/2) 39 – 49.

Federal Department of Agricultural Land Resources (FDALR), Soil Survey Division. (1990), *Soils Map of Nigeria*, Kaduna, Nigeria.

Garba, Y. I., Danjuma, M. N., & Zakariya, M. (2023). *Assessment of Soil Quality for Agro-Diversification in Kaduna State, Nigeria*, UMYU Scientifica, 2 (4) 1 – 8. <https://doi.org/10.56919/usci.2324.001>

Goma, D. (2024). *Analysis of rainfall and temperature changes on agricultural production in Kaduna State, Nigeria*, Kashere Journal of Geography and Sustainable Environment 1 (1) 51-73.

Gorzalczany, M.B. (1987). A method of inference in approximate reasoning based on interval valued fuzzy sets, *Fuzzy Sets and Systems*, Elsevier, 21 (1) 1-17.

Hiikyaa, N. A. (2024). Assessment of Nutrient Flows in Maize-Based Farming System by Small holder Farmers for Sustainable Production in Ikara, Kaduna State, *Science World Journal* 19 (1) 9-12. <https://dx.doi.org/10.4314/swj.v19i1.2>

Ibrahim, J. A., Mbaya, A. L., Akande, D., Agaku, D. T., & Haruna, S. N. (2020). *Impact of toposequence on soil properties and classification in Zaria, Kaduna State, Northern Guinea Savanna, Nigeria*, EQA – International Journal of Environmental Quality (38) 48–58.

Isah, A. I. (2019). The Concept of α -Cuts in Multi Q-fuzzy sets, *Science World Journal* 14 (2) (2019) 42-44.

Isah, A. I. (2020). Multi-Fuzzy Set Relational Structures, *FUDMA Journal of Sciences* 4 (1) (2020) 662 –667.

Jagtab, S. S., Abamu, S. J., Kling, J. G. (1999). Long-term assessment of nitrogen and variety technologies on attainable maize yields in Nigeria using CERES-maize, *Agricultural Systems*, Science Direct, Elsevier, 60 (2) 77-86.

Jimoh, I. A., Aliyu, J., Sabo, A. T., & Yusuf, Y. O. (2018). *Land suitability evaluation of Kubanni floodplain for rice production in Zaria, Kaduna State, Nigeria*. *Nigerian Journal of Basic and Applied Sciences*, 26(1), 46–54.

Kang, Y., Ozdogan, M., Zhu, X., Ye, Z., Hain, C., and Anderson, M. (2020). Comparative assessment of environmental variables and machine learning algorithms for maize yield prediction in the US Midwest. *Environ. Res. Lett.* 15, 064005. <https://10.1088/1748-9326/ab7df9>

Khaki, S., and Wang, L. (2019). Crop yield prediction using deep neural networks. *Front. Plant Sci.* 10, 621. <https://10.3389/fpls.2019.00621>

NAERLS and FMARD, (2021). National Report of Wet Season Agricultural Performance in Nigeria. Nigeria, Zaria: NAERLS Press.

Suleiman. U. B., Abdulhamed, A. I., Musa, A. J. and Yelwa, S. A. (2019). Decadal Analysis and Estimation of Temperature Changes in Northern Senatorial Zone of Kaduna State-Nigeria, *FUDMA Journal of Sciences* 3 (3) 509 –518.

StatsClimat. (2025). Comprehensive climate report: Kaduna (Nigeria). StatsClimat Kaduna Climate Report.

Tadama, M. H. (2024). The Impact of Climate on Maize Yield in Chikun Local Government Area of Kaduna State, Nigeria, *Kaduna Journal of Geography*, 6 (1) 103-115.

Wang, K., Han, Y., Zhang, Y., Zhang, Y., Wang, S. Tang, F. Liu, C., Zhang, D., Lu, T., Zhang, L. and Liu, Z. (2024). Maize yield prediction with trait-missing data via bipartite graph neural network. *Frontiers in Plant Science*. 15:1433552. <https://doi.org/10.3389/fpls.2024.1433552>

Yang, X., Lin, T. Y., Yang, J., Lia, Y. and Yu, D. (2009). Combination of interval-valued fuzzy set and soft set, *Computers and Mathematics with Applications* (58) 521-527.

Zadeh, L. A. (1965). Fuzzy sets, *Information and Control*, 8, 338 - 353.

Zadeh, L.A. (1975). The concept of a linguistic variable and its application to approximate reasoning - I, *Information Sciences*, Elsevier, 8 (3) 199 - 249.

Zhang, Q., Zhao, X., Han, Y., Yang, F., Pan, S., Liu, Z., Wang, K. and Zao, C. (2023). Maize yield prediction using federated random forest, *Computers and Electronics in Agriculture*, *Volume 210*, <https://doi:10.1016/j.compag.2023.107930>

