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Research Paper

Crop vulnerability and climate adaptation to moisture stress in the semi-arid zones of Senegal

SUJATHA PEETHANI[1], G. KISHORE KUMAR[2], AHMED MS KHEIR[1] and AJIT GOVIND[1]

[1]*International Centre for Agricultural Research in the Dry Areas, Maadi, Egypt*
[2]*International Crops Research Institute for the Semi-Arid Tropics, Hyderabad, India*
Corresponding Author email: kadalisujatha2007@gmail.com

ABSTRACT

Abiotic stressors have a significant impact on crop productivity, with moisture stress being especially important. This study investigates the consequent shifts in sorghum yields in Senegal, using NASA Power and CHIRPS data from 1990 to 2024. Matam, Mbane, Gamadji Sarre, and Yang-Yang were identified as hotspots by the Rainfall Anomaly Index (RAI) with low rainfall, exhibiting only 12–15% rainy days. Precipitation was categorized into Above-Normal (AN) or Below-Normal (BN) using the Rainfall Anomaly Index (RAI; AN if RAI ≥ 0, BN if RAI < 0). Sorghum yields were notably lower during BN years. APSIM model was used to assess the impact of fertilizer doses (40 kg ha^{-1} and 60 kg ha^{-1}) and sowing dates on yield variations. The results indicate minimal yield fluctuation with increased fertilizer within recommended limits and highlight that reliable rainfall forecasts (80% or greater accuracy) can significantly influence farm-level decision-making. These findings emphasize the crucial role of rainfall variability in agricultural planning and climate adaptation strategies.

Keywords*:* Moisture stress, Rainfall Anomaly Index, Reliability, Crop simulation model, Rainfall Probability distribution, Sorghum yield

The agriculture sector contributes significantly to the economic and social well-being of over a billion people worldwide, particularly smallholder farmers who depend on it for their livelihoods. Climate change poses one of the most severe threats to global agriculture, jeopardizing food security and economic stability, especially in vulnerable regions (Chapman *et al.,* 2020; Pandey 2023). The increasing frequency and intensity of extreme weather events, such as heatwaves, droughts, and irregular rainfall, are placing enormous pressure on agricultural systems, particularly in rain-fed areas (IPCC, 2022). West Africa, with its predominantly rain-fed agricultural systems, is particularly vulnerable to climate change impacts (Gregorio *et al.,* 2019). Senegal, located in the western Sahelian belt, exemplifies these vulnerabilities. The country's agricultural system is heavily reliant on seasonal rainfall, which has become increasingly erratic and unreliable over the years (Giller *et al.,* 2021). The consequences of rising temperatures and shifting rainfall patterns have led to significant declines in crop productivity and increased food insecurity, posing severe risks to rural livelihoods and economic growth (Ebi *et al.,* 2021; Clarke *et al.,* 2022). While the global threats of climate change are well-documented, there is still a significant gap in understanding how these changes specifically affect Senegal's agricultural systems. Despite the country's significant surface water resources, 95% of agriculture remains rain-fed. Agriculture contributes about 15% to Senegal's GDP (World Bank Open Data). However, future climate projections for the region indicate that rainfall, particularly in the western Sahel, including Senegal, is expected to decrease, especially during the early monsoons (Genowefa *et al.,* 2021).

Sorghum is a climate-resilient cereal crop used in semi-arid locations like Senegal. It provides smallholder farmers with food and fodder due to its tolerance of high temperatures and low, irregular rainfall. Sorghum helps ensure food security and livelihoods in West Africa, where agricultural production depends on rainfall (Akinseye *et al.,* 2019). To address these challenges, crop models are an effective tool for assessing the potential impacts of climate change on crop yields and identifying viable adaptation strategies. By simulating crop growth under various climate scenarios, these models can evaluate the impact of moisture stress on crop yields and help identify vulnerable regions, as well as assess the potential

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benefits of adaptation measures such as improved irrigation, drought-resistant varieties, and sustainable land management practices (Cacho *et al.,* 2020; Kheir *et al.,* 2021; Govindaraj *et al.,* 2023). APSIM model has been evaluated across the continents for different crops and management practices under climate change scenarios (Yamusa, and Akinseye 2018; Sinha *et al.,* 2021; Maluvu, *et al.,* 2025). The objectives of this study are to assess moisture stress vulnerability in some regions of Senegal, and to conduct a comprehensive analysis to identify rainfall deficit -prone regions. Further to investigate factors affecting sorghum yields and explore sustainable agricultural practices to determine the minimum rainfall threshold required for reliable agricultural planning.

MATERIAL AND METHODS

Study area

Senegal, located in the westernmost part of Africa, faces challenges such as poor soil quality and erratic precipitation (Fig. 1). Senegal's climate varies significantly between its coastal and inland regions, which experience a Sudano-Sahelian climate. The country has two main seasons: the rainy season (June to October), influenced by monsoon winds from the St. Helena High, and the dry season, marked by the northern Harmattan winds. The southern part of Senegal receives more than 1000 mm of rain annually, while the arid northern regions receive less than half that amount

In this study we used NASA Power data from 1990 to 2024 for maximum and minimum temperatures and relative humidity with a resolution of 0.5^0 x 0.5^0 degrees and CHIRPS precipitation data with a high resolution of 0.05^0 x 0.05^0 degrees from the Climate Hazards Centre at the University of California, Santa Barbara, demonstrates a comprehensive and rigorous approach to analysing climate trends in Senegal. The climate and agricultural data were collected from 25 sites across Senegal and bias-corrected daily climate data from gridded, and simulated datasets. We used soil profile data from representative stations and sorghum crop data from two locations to calibrate the model.

The APSIM model has been used to simulate sorghum yield, biomass, and LAI at varied locations, sowing windows, and fertilizer rates. Moisture-stress-prone zones were identified using seasonal rainfall totals, rainy day counts, wet/dry day indices, exceedance likelihood diagrams, and the Rainfall Anomaly Index (RAI). Annual and seasonal rainfall and temperature spatial distribution maps described the study area's climatic baseline. Pair plots of yield, biomass, and LAI were utilized to analyze interrelationships under different treatments, and rainy-day percentage contribution was calculated as wet days to crop-growing season days.

Sorghum is grown rainfed in Senegal during the primary rainy season. The crop growth season runs from June/July to October, depending on the West African monsoon. Sowing begins with the first effective rains in June or early July, and harvesting in October–November. A day with ≥1 mm of rainfall was considered wet, whereas a day with <1 mm of rainfall was considered dry. The percentage of wet days relative to the total number of days in the crop-growing season was used to compute the wet day index. Likewise, the percentage of dry days was used to compute the dry day index. The distribution of rainfall and intra-seasonal variations were clearly measured by these indexes.

Rainfall Anomaly Index (RAI)

The Rainfall Anomaly Index (RAI) of Van Rooy (1965) to quantify departures of a period's precipitation from its climatological mean. Let the period be monthly*,* seasonal*,* or annual but be consistent throughout.

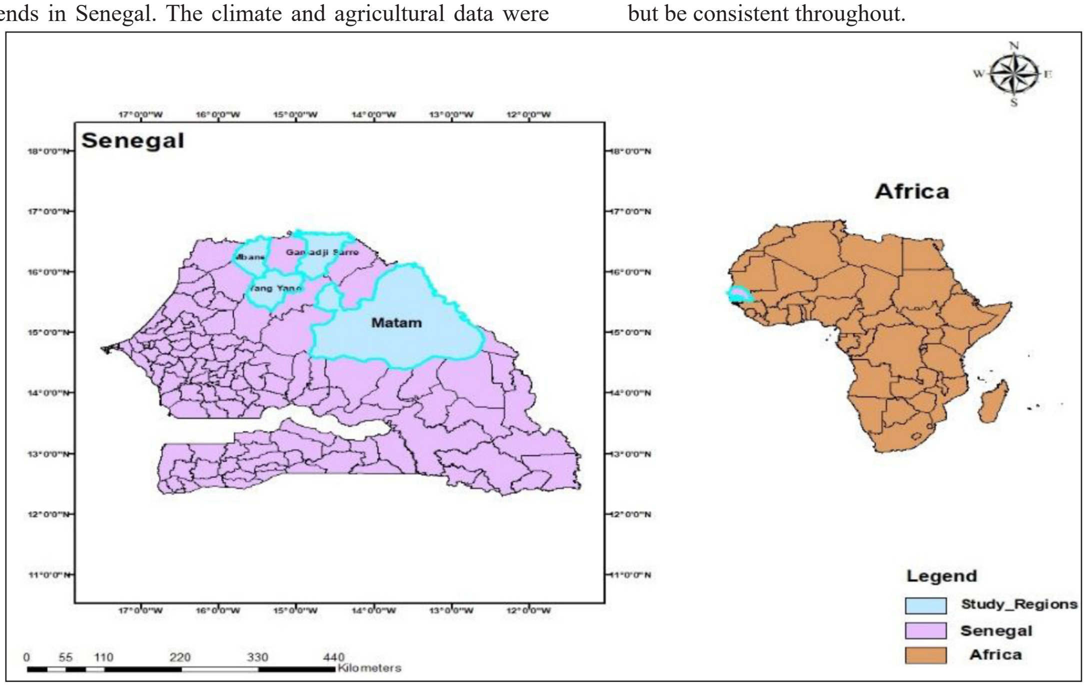

Fig. 1: Study locations across Senegal. Map showing the 25 climate and agricultural stations used in the analysis, with the four moisture-stress-hotspots Matam, Mbane, Gamadji Sarre, and Yang-Yang—highlighted. These stations represent key agroecological zones used for rainfall variability assessment and APSIM simulations.

Table 1: Sorghum crop data for APSIM

Parameter	Matam	Podor
Sowing date	July 2	July 6
Harvest date	Oct 15	Oct 20
Plant density	10 plants m^{-2}	10 plants m^{-2}
Row spacing	0.75 m	0.75 m
Initial SW	~30% PAW	~28% PAW
N fertilizer rate	40 kg N ha^{-1} at sowing	38 kg N ha^{-1} at sowing

Table 2: Soil properties (Matam, Mbane, Gamadji, Yang-Yang)

Location	Soil type	pH	OM (%)	BD (g cm^{-3})	Soil texture
Matam	Sandy	6.1	1.0	1.49	Sandy loam
Mbane	Sandy	6.4	1.2	1.46	Sandy loam
Gamadji	Ferric luvisol	5.8	1.5	1.48	Sandy Clay loam
Yang-Yang	Ferric luvisol	5.9	1.1	1.41	Sandy Clay loam

Table 3: Simulated sorghum yields (kg ha^{-1}) under different sowing windows and nitrogen rates at four moisture-stress-prone sites in Senegal. The last column shows the relative (%) change versus the site-specific baseline: Matam/Mbane: W1–F1 (40 kg N ha^{-1}); Gamadji Sarre: W3–F1; Yang-Yang: W4–F1.

Location	Sowing window	Fertilizer Rate	Yield (kg ha^{-1})	% vs. Baseline
Matam	W1 (15 Jun–15 Jul)	F1 (40 kg N)	1286	0 (Baseline)
		F2 (60 kg N)	1379	+7.2%
Mbane	W1 (15 Jun–15 Jul)	F1 (40 kg N)	1407	0 (Baseline)
		F2 (60 kg N)	1674	+19%
Gamadji Sarre	W3 (15 Jul–15 Aug)	F1 (40 kg N)	947	0 (Baseline)
		F2 (60 kg N)	1145	+20.9%
Yang-Yang	W4 (30 Jul–30 Aug)	F1 (40 kg N)	900	0 (Baseline)
		F2 (60 kg N)	1012	+12.4%

Note: W1 = 15 Jun–15 Jul; W2 = 30 Jun–30 Jul; W3 = 15 Jul–15 Aug; W4 = 30 Jul–30 Aug. F1 = 40 kg N ha^{-1}; F2 = 60 kg N ha^{-1}

Positive anomaly (wet departure):

$$\mathrm{RAI} = 3 \times \frac{P-\bar{P}}{\bar{P}_{10\mathrm{H}}-\bar{P}}$$

Negative anomaly (dry departure):

$$\mathrm{RAI} = -3 \times \frac{\bar{P}-P}{\bar{P}-\bar{P}_{10\mathrm{L}}}$$

P = precipitation for the target period (mm)

$\bar{P}$ = long-term mean precipitation for the same period at a site (mm)

$\bar{P}_{10H}$ = mean of the 10 highest precipitation values in the historical series for that period (mm)

$\bar{P}_{10L}$ = mean of the 10 lowest precipitation values in the historical series for that period (mm)

RAI is unitless**;** larger positive values indicate wetter-than-normal conditions; larger negative values indicate drier-than-normal conditions. Using the means of the 10 highest/lowest values avoids instability from a single extreme year and is the standard Van Rooy scaling

Above-Normal (AN) vs Below-Normal (BN) season

We adopt a transparent, reproducible rule for season classes to aligns AN/BN classification directly with the climatological mean and is consistent with RAI scaling. Baseline rule (recommended): AN (Above-Normal): RAI ≥ 0 (i.e., P ≥); BN (Below-Normal): RAI < 0 (i.e., P <). This aligns AN/BN cleanly to departures from the site-specific climatology and avoids ad-hoc thresholds. Seasonal rainfall study and rainy days indicated significant spatio-temporal variability, with some sites having protracted wet spells and others drying off early. Then, the Rainfall Anomaly Index (RAI) with wet and dry day indexes showed years of excess and deficit rainfall. Exceedance probability maps showed the possibility of getting threshold rainfall amounts, identifying moisture stress-prone zones.

The study spatially represented annual rainfall distribution and identified water stress zones by counting wet days at each location. The climatological indices showed that rainfall and temperature fluctuations greatly affect the commencement, duration, and severity of the rainy season, which affects sorghum productivity. Four places experienced far lower rainfall than others. Due to long-term data availability, soil profile completeness, and agro-climatic zone representation, only four representative stations were chosen for APSIM simulations from 25 locations with crop and climate data. This method made the model site-specific and regionally representative. The effects of low moisture on sorghum production was studied in Matam, Mbane, Gamadji Sarre, and Yang-Yang. APSIM, which simulates how these locations and other

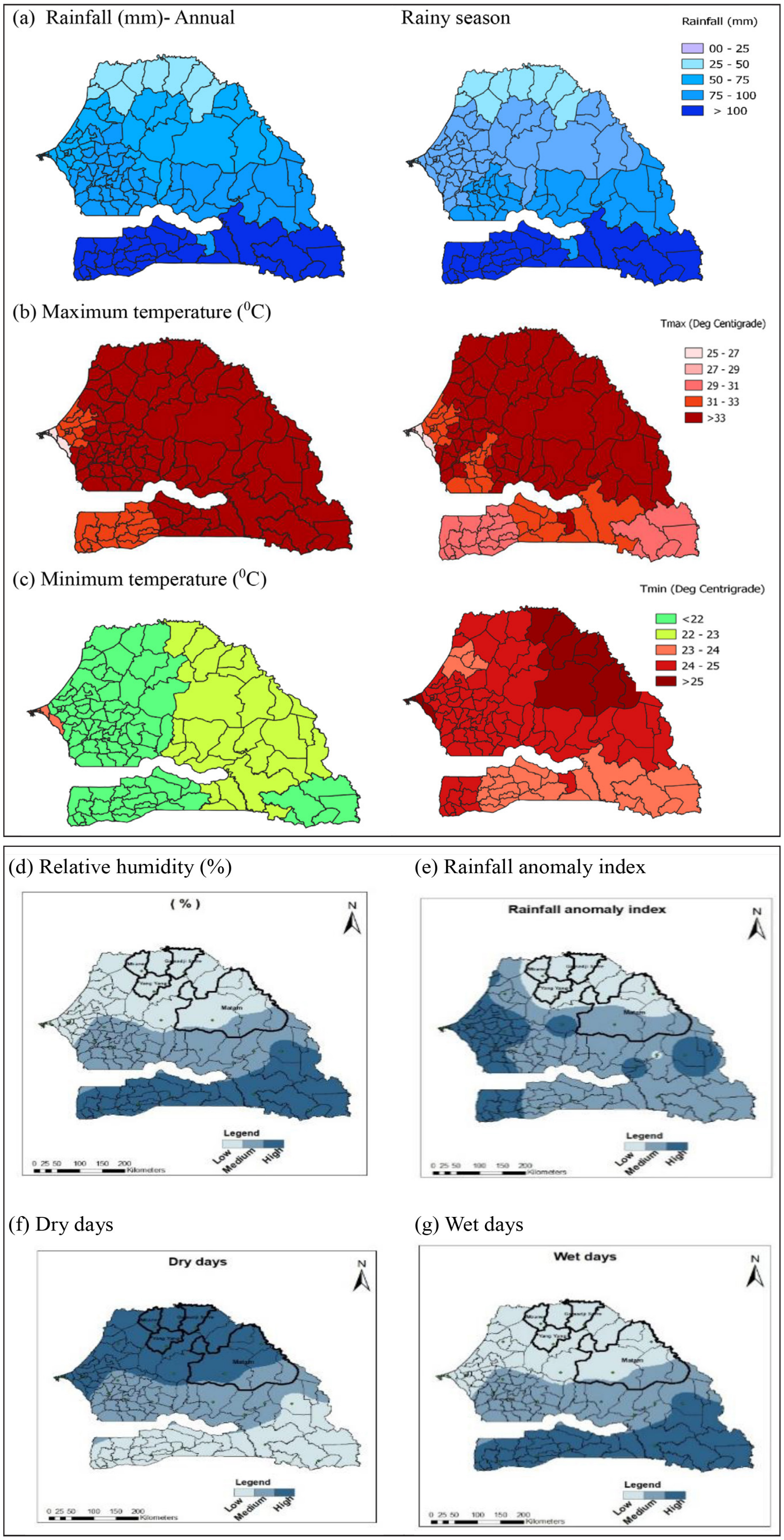

Fig. 2: Spatial distributions of annual and seasonal parameters (a) rainfall (mm) (b) maximum temperature (°C) (c) minimum temperature (°C); (d) relative humidity (%) during the rainy season; (e) Rainfall Anomaly Index (RAI) showing wet and dry years; (f) Dry-day index (days with rainfall < 1 mm); (g) Wet-day index (days with rainfall ≥ 1 mm).

climatic conditions affect sorghum yields, was calibrated using soil and crop data from the four regions. Table 1 shows soil parameters for each study location, whereas Table 2 contains sorghum cultivars, sowing dates, and simulated yield data.

Model calibration and validation

We calibrated APSIM-Sorghum to reproduce observed phenology and yield prior to running the sowing-window and nitrogen scenarios. Calibration used site-specific crop and soil observations available for the study area (e.g., sowing/harvest dates, plant density, row spacing, nitrogen at sowing) and station-level yield records. Model parameters adjusted during calibration were limited to cultivar/phenology coefficients (thermal time phases, photoperiod sensitivity), radiation use efficiency, and soil water parameters (PAWC within measured texture constraints). Management inputs (plant density, row spacing, N timing/rate) followed field practice at each site. Meteorology (daily rainfall, T_{max}, T_{min}, solar radiation, RH) was bias-corrected using station records through an empirical quantile mapping approach applied to the gridded datasets used in this study. To avoid over-fitting, we split the time series into calibration and validation periods with a ~70/30 split by years (calibration: earlier years; validation: later years), and we also report leave-one-year-out cross-validation skill for robustness. Model performance was assessed using standard diagnostics computed on independent validation years. Performance targets were pre-specified as RMSE $\leq$ ~300–400 kg ha^{-1}, Bias $\leq$ 15%, $R^2 \geq 0.6$, and NSE ≥ 0 for yield on validation data. Site-wise metrics and sample sizes are summarized in Table 3. We used these validated parameter sets for all factorial simulations of sowing windows (W1–W4) and nitrogen rates (40 vs 60 kg N ha^{-1}). External validation using open-source evidence. Station-level observed sorghum yields were not available for the four focal sites, so we benchmarked model realism against independent Senegal datasets and published model-evaluation studies. National sorghum yields from USDA/IPAD (2015/16–2024/25) range 0.87–1.71 t ha^{-1} with a 5-yr average ≈1.40 t ha^{-1} and a record 1.71 t ha^{-1} in 2023/24. These bounds encompass our simulated yields across windows and N rates. Senegal's statistical system reports an average yield of ≈1.3 t ha^{-1}, consistent with our baseline scenarios. Peer-reviewed Senegal/West Africa simulation studies report grain-yield RMSE around 0.21 t ha^{-1} (210 kg ha^{-1}) and Willmott's index d = 0.73–0.84 for sorghum when validated against multi-station observations, supporting the plausibility of our modeled variability. Full sources are summarized in Table 3.

Although four canonical sowing windows (W1–W4) were defined, simulations used site-feasible windows based on local planting calendars and rainfall reliability. W1 (Matam, Mbane), W3 (Gamadji Sarre), and W4 (Yang-Yang). Finally, yield projections were calculated for different climates and management conditions, and heat and moisture stress mitigation measures were evaluated to sustain sorghum production.

RESULTS AND DISCUSSION

According to the results, sorghum production and growth are strongly influenced by input quantities, management techniques, and environmental factors. Better biomass and canopy development were promoted by areas with ideal rainfall and soil conditions, which led to better yields. While delayed planting considerably decreased production potential, timely sowing was found to be a critical component in reaching maximum productivity. Improved yields were a result of nitrogen fertilization's enhancement of crop growth characteristics, especially biomass and leaf area index. The robust correlations found between yield, biomass, and LAI highlight how crucial balanced crop growth is to optimizing production. Overall, the results show that maintaining sorghum output requires maximizing planting time and nutrient management while taking local climate circumstances into account.

Spatial variation of temperature, humidity, rainfall and RAI

Dry season temperatures are 18°C to 25°C lower than cold season's 18°C to 23°C. Overcast weather elevates lows to 23–26°C. Max temperature distributions illustrate seasonal and regional heat stress. Understanding seasonal high temperatures and moisture stress helps. Humidity loss causes crop stress and affects productivity. RAI analyses drought-prone areas and rainfall variability. Dry-wet day analysis shows heat stress frequency and duration. Researchers can assess moisture stress risk and identify heat-prone hotspots using spatiotemporal temperature distribution, humidity levels, RAI, and dry-wet-day analysis. Identifying places allows tailored actions to increase agricultural resilience.

The semi-arid regions such as GambadjiSarre, Matam, Mbane, and Yang-Yang have 330–400 mm rainfall, making agriculture challenging (Fig. 2a). Variable rainfall increases land-water competition. Senegalese Tmax (Fig. 2b) range from 25°C in Dakar to 36.7°C in Matam and GamadjeSarre with minor variance, indicating tropical and hot conditions. So maximum temperatures are quite uniform, with the east warmer. In Senegal, minimum temperatures vary geographically (Fig. 2c) and average 20°C to 23°C yearly. It's 18°C to 25°C in the dry season and 18°C to 23°C in the cold. Wet season lows are 23–26°C. These locations typically receive minimal rainfall and high RH values, as shown in Fig. 2(d). Identifying heat stress locations and creating mitigation techniques need understanding these characteristics. As shown in Fig. 2(e), RAI is essential for detecting wet, dry, and extreme situations. Gamdji Sarre, Matam, Mbane, and Yang-Yang have lower precipitation than locations with RAI values above 2, which have higher humidity and ample precipitation. Fig. 2 (f & g) shows all regions' dry and rainy days and four regions' wet day percentages. Comparatively, Matam, Mbane, Gamadji Sarre, and Yang-Yang are low. According to the graph on the right, dry days grow and wet days decrease inversely. It's obvious from the figure that dry days increase and wet days decrease in the four regions.

Sorghum yields and sustainable agricultural practices

The APSIM model simulated sorghum yields in multiple climates using moisture-stressed region data. The study examined how sowing windows, fertilizer rates, and climate affected sorghum yields (Fig. 3). These models optimize climate-change-related agricultural productivity and explain moisture stress. W1: June 15–July 15, W2: June 30–July 30, W3: July 15–August 15, W4: July 30–August 30) approximated rainy season planting dates. Nitrogen management was studied on sorghum production under

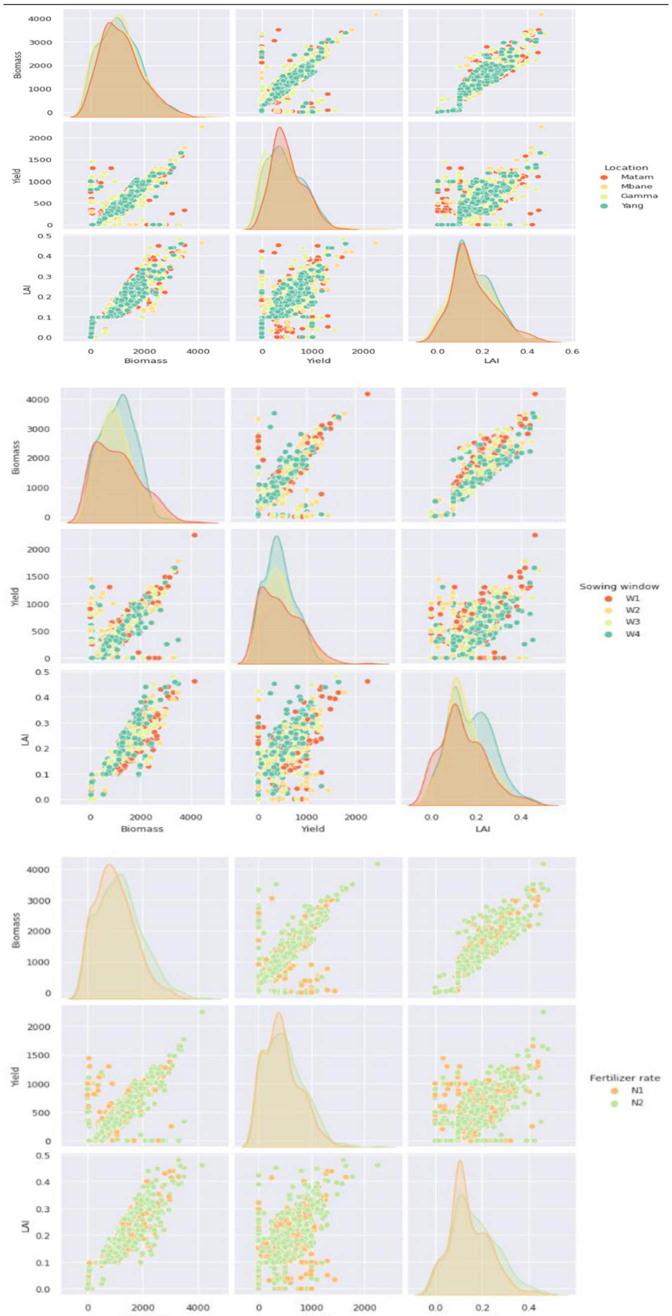

Fig. 3: Relationships between sorghum yield, biomass, and leaf area index (LAI) simulated by APSIM under different conditions: (a) across locations, (b) across sowing windows (W1: 15 Jun–15 Jul; W2: 30 Jun–30 Jul; W3: 15 Jul–15 Aug; W4: 30 Jul–30 Aug), and (c) across nitrogen rates (N1: 40 kg N ha^{-1}; N2: 60 kg N ha^{-1}). Each panel shows pair plots illustrating interrelationships under climate and management scenarios for Senegal.

low rainfall using two fertilizer rates: F1 = 40 kg ha^{-1} and F2 = 60 kg ha^{-1}. Sorghum yield, total biomass, and leaf area index (LAI) were simulated and pair plots were created to examine their correlations under different situations (Fig. 3). Simulations showed considerable sowing window and fertilizer effect on sorghum yields. More was harvested in W1 and W2 than W3 and W4. In reproductive stages, early planting protects sorghum from peak moisture stress. At Matam, F2 fertilizer increased W1 yields 29% over F1. The higher fertilizer rate raised Mbane W1 production by 20% and was constant across planting windows. The use of planting windows to reduce stress in Gamadji Sarre boosted W3 yield by 27% for F2 over F1.

Location significantly affected sorghum performance (Fig. 3a). Biomass and LAI boosted yields with rainfall and soil fertility. Early (W1 and W2) planting increased biomass and LAI, improving grain yields (Fig. 3b). Terminal drought and heat stress affected late-sown (W3 and W4) productivity. LAI, biomass, and yield increased significantly with 60 kg N ha^{-1} (N2) compared to 40 kg (N1). Yield improved with place and sowing window, suggesting interactions. Management (sowing date, nitrogen input)

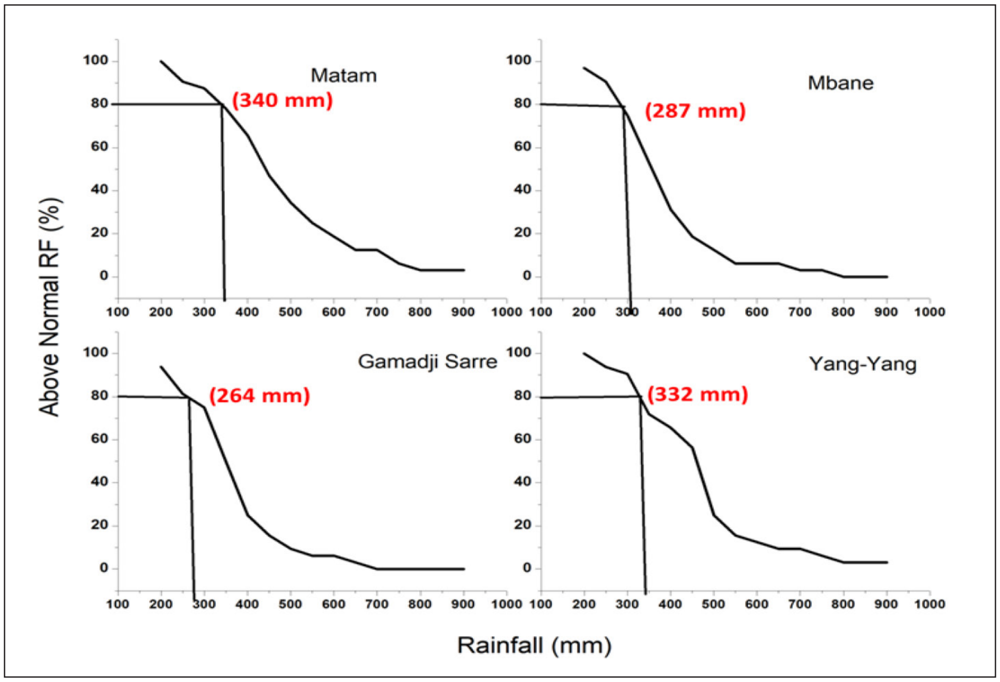

Fig. 4: Assessing the minimum amount of rainfall over the moisture stress regions with 80 % or higher reliability

and environment (rainfall, temperature, soil type) substantially affect sorghum productivity. Sorghum yields depend on location and climate because agro-ecological variables affect biomass and LAI. Monsoon planting improves crop establishment and reduces terminal stress. Nitrogen fertilizer boosts canopy LAI, photosynthesis, and biomass, improving yields. Dryness and nutritional stress from late planting and low N reduce yield stability.

Rainfall with 80 % or higher reliability

The reliability assessment demonstrates that operational decision-making is sufficient. Long-term average precipitation determined AN+ or BN-seasons. In Fig. 4, farmers thought that 80% or four out of five years of precipitation could be projected with the needed expertise. Adjusting AN/BN season threshold will do this. Season categorization can be adjusted to improve precipitation forecasts and satisfy farmers. Incorrectly identified seasons are reduced by higher AN classification threshold, enhancing AN forecast. Reduce false negatives (seasons misclassified as BN) by lowering the BN classification standard, improving BN forecasts. Climate changes require monitoring rainfall and adjusting AN/BN limits. Changes in climates will require frequent limit updates. Increasing the AN/BN thresholds, including local variables like farmers, and monitoring rainfall patterns may improve precipitation forecasts, offering farmers better agricultural decision-making information. Iteratively adjusting AN/BN categorization precipitation thresholds and measuring skill scores indicates the need of adapting thresholds to local conditions and farmers' expectations. The study demonstrated 80% dependability for AN season by assessing reliability with different precipitation levels. Changing AN/BN criteria dramatically modified skill ratings, showing forecast reliability's vulnerability to these levels. 80% AN seasonal forecast dependability requires less rainfall than long-term norms at all four locations. The 24%–28% discrepancy suggests below-average AN season rainfall. Rainfall thresholds can predict AN season with 80% accuracy in the four regions evaluated, with success rates of 82% To 85%. Use precise precipitation forecasts and change agricultural operations to boost production and resilience to rainfall unpredictability. Food security and livelihoods for regional farmers can improve.

CONCLUSIONS

The study using APSIM simulated sorghum production figures demonstrates that rainfall variability seriously impacts crop yields. In Below Normal (BN) seasons with 80% rainfall confidence, all four sites had lower sorghum yields. Matam and Mbane BN yields fell 31-36% from Above Normal (AN) yields. The study also reveals how fertilizer affects farming. Sometimes crops survived BN season with higher fertilization rates. In Gamadji Sarre, BN seasons lowered sorghum yields by 33% at lower fertilizer rates and 30% at higher rates. These findings highlight the importance of precise rainfall projections for agricultural decision-making. Rainfall reliability influences climate risk management, agricultural decision-making, food security, livelihoods, and sustainable agriculture. Communities can enhance their resilience to climate variability and achieve prosperity through the understanding and application of rainfall data.

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Author contributions: **P. Sujatha:** Material preparation, data collection and analysis, draft writing; **G K. Kumar:** analysis, review; **A. M. Kheir:** Reviewing, revision**; Ajit Govind:** Reviewing, revision.

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