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Analysis of Drought Characteristics and their relationship with Crop yield in Northwestern Nigeria

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Abstract:

Drought affects virtually all climate regions, with a profound impact on arid and semi-arid regions worldwide. This study examines drought characteristics and their relationship with crop yield estimation in Northwestern Nigeria, using monthly rainfall and minimum and maximum temperatures from 1980 to 2021, while crop yield information is from 2009 to 2021. The Standardized Precipitation Index (SPI) and the Standardized Precipitation Evapotranspiration Index (SPEI) were used to characterize drought. Correlation and regression analyses were performed with SPI SPEI and crop yield estimation. Results of correlation and regression analysis show the behavior of drought indices varies: SPEI better predicts yield at Kaduna (R^2 = 80.3%) and Kano (R^2 = 56.7%), while SPI performs better at Jigawa (R^2 = 66.6%) and Kano (R^2 = 66.6%). Hence, it is sensitive to drought quantification, whereas SPI can serve as an indicator of regional crop production. Crop yield of maize shows a highly positive linear correlation with SPEI in Kaduna (0.774) and a very low correlation in Jigawa (0.191). These factors can be used effectively to monitor and assess food grain production, thereby enabling the adoption of appropriate agricultural practices to minimize the effects of drought.

Keywords: Drought, Crop yield, SPI, SPEI, Relationship.

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1. Introduction

Climate change increases the frequency and magnitude of hydro-meteorological hazards, such as drought and floods, that affect virtually all regions of the world. Drought has a profound impact on crop yield and the subsistence farming economy in arid and semi-arid lands of developing countries. (Hamal et al., 2020). Global assessment report on disaster risk reduction (2023) observed that drought phenomena are dramatically increasing with great effect on global food security, employment, education and about two billion people are now living under water stress condition and where 80% are at the risk of crop failure, resulted to the hunger in sub- Saharan Africa and South east Asia reported by United Nations Office for Disaster Risk Reduction (UNDRR, 2023). Drought has long been recognized as one of the most insidious causes of human misery, and it is a natural disaster that annually causes economic losses for farming communities worldwide (Narasimhan & Srinivasan, 2005; Qaisrani et al., 2021). Worldwide, drought accounts for 7.5% of natural disasters and is considered the second-most geographically widespread hazard after floods (UNDRR, 2007). The percentage of areas affected by serious drought doubled from the 1970s to the early 2000s (Nagarajan, 2009). Understanding the mechanisms underlying these climate features can improve the ability to make timely seasonal predictions of drought events and provide useful insights for resource planners, system managers, and policymakers to help mitigate drought impacts. (Vogt and Gordon, 2021). The study conducted by (Das et al., 2020) revealed an increase in the mean yield of crops, which was attributed to the suitable temperature profile and the lack of significant water stress during the growing seasons of different crops. Recent scientific evidence underscores the alarming acceleration in drought trends. According to the Intergovernmental Panel on Climate Change (IPCC), global warming of 1.1°C above pre-industrial levels has already intensified hydrological extremes such as droughts (IPCC, 2023).

There is practically no climatic region in which droughts of varying intensities have not occurred in recent decades, largely due to climate change. According to Tadić et al (2015), the UN considers drought to be the greatest threat facing the world in the 21st century. In Africa, rising global temperatures accompanying climate change have intensified the hydrological cycle and led to drier dry seasons, thus increasing the risk of more extreme and frequent droughts. To validate this fact, the World Meteorological Organization (WMO, 2022) confirmed that the past seven years have been the warmest period. This has significantly increased the frequency and severity of extreme hydrological events, such as floods and droughts, worldwide (Leng et al., 2016). The Sudan Sahelian Zones (SSZ) in West Africa (including Northwestern Nigeria) are characterized by alternating periods of extreme dryness (i.e., drought) and wetness on annual and decadal time scales. Based on previously reported consequences of catastrophic droughts, it is clear that climatic variability, especially droughts, has made it difficult for most rural dwellers (farmers and herders) in the SSZ, including Northwestern Nigeria, to sustain their livelihoods. Tarhule & Lamb (2003) highlighted that the droughts that ravaged the area in the period 1960s-1990s led to a very serious ecological decline, the decimation of livestock herds, widespread food scarcity, mass migrations, and the great loss of human lives.

A recent study (Okoduwa & Mokhtarisabet, 2025) observed significant fluctuations in drought severity and vegetation stress in the Sahelian region, with critical periods and persistent aridity in Borno, Yobe, and Gombe States. The impact of climate variability, especially droughts, has created food crises in arid lands, which are always linked to high vulnerability to acute health crises (Pérez-Sánchez & Senent-Aparicio, 2018). Persistent drought in Northwestern Nigeria delays the onset of rains, leads to early cessation of the rains, and shortens the rainy season, including pronounced dry spells, which have caused low agricultural productivity in the region, since it is mostly dependent on rain-fed agriculture.

Drought is classified into four main types: meteorological, hydrological, agricultural, and socioeconomic droughts (WMO, 2006). A study by Mishra & Singh (2010) introduced the term groundwater drought as a distinct type and considered it an aspect of hydrological droughts (Zhu et al., 2016). In general, meteorological drought is followed by agricultural drought, then hydrological drought. (Wilhite & Glantz, 2019). A prolonged hydrological drought will then lead to socioeconomic changes that may reach the level of famine, triggering migration and large-scale refugee situations. (Mishra & Singh, 2010; Abdourahamane, 2018). It is very difficult to provide a precise, universally accepted definition of drought due to its varying characteristics and impacts across regions worldwide, including rainfall patterns, human responses, resilience, and diverse academic perspectives. (Belal et al., 2014) attributed the obstacle of having a precise definition for hydro-meteorological variables and socioeconomic factors to the stochastic nature of water demand in different regions around the world.

The indicators commonly used to identify droughty conditions are vegetation health, rainfall, evaporation, streamflow, temperature, crop information, and soil moisture (Svoboda & Fuchs, 2016). Studies have shown that farmers plant their crops about 3-4 times due to early-season drought (Turco et al., 2013). Reports on crop conditions also indicate the severity of the drought. When crops are wilting, it indicates soil moisture stress. Other factors that affect crop yield were grouped into three basic categories. (Ngoune Liliane & Shelton Charles, 2020): technological (agricultural practices, managerial decisions), biological (diseases, insects, pests, and weeds), and environmental (climatic conditions, soil fertility, topography, and water quality).

The assessment of drought impacts on specific crops under certain conditions is a key factor in identifying farm-level adaptability and estimating the viability of alternative crop yield options. (Tigkas et al., 2020). Several studies have examined the impacts of droughts on crop growth and development at different levels, including soil moisture uptake, shoot and root growth, several plant processes such as photosynthesis, respiration, and plant water uptake, and final yield. (Dalezios et al., 2017). The detrimental effects of drought on rice, maize, and soybean yields in Southern Brazil were measured in a related study (Miyamoto & Hackmann, 2025). They found that drought negatively affected rice, maize, and soybeans. The Standardized Precipitation Index (SPI) was used to assess the impacts of extreme events on agricultural productivity without incorporating the Standardized Precipitation Evapotranspiration Index (SPEI). Findings reveal a consistent negative association between drought and crop yields, with each crop exhibiting a distinct sensitivity profile.

Recent studies have examined crop damage using drought indices such as the Standardized Precipitation Index (SPI) (Barideh & Nasimi, 2025). In a related analysis, Bezdan & Bezdan (2019) employed multiple regression techniques to assess the relationship between crop yield and drought, incorporating the Standardized Precipitation Index (SPI), Standardized Temperature Index (STI), and Standardized Precipitation Evapotranspiration Index (SPEI). Their findings demonstrate that SPEI exhibits a stronger correlation with de-trended crop yields than SPI or STI. Specifically, SPEI showed greater sensitivity during critical crop growth stages and explained between 40% and 74% of the variability in de-trended yields.

Furthermore, studies such as Shiru & Shahid (2018) utilized satellite-derived rainfall and temperature data, while others, including Adepoju et al. (2022), focused primarily on rainfall data in relation to crop yield estimation. However, reliance on precipitation-only indices such as SPI may be inadequate, as they do not account for temperature effects, which are critical for understanding evapotranspiration and the overall water balance. As highlighted by Svoboda & Fuchs (2016), integrating both precipitation and temperature provides a more comprehensive assessment of drought impacts on agricultural productivity.

Early studies primarily focused on the influence of climatic variables on crop yields, either by analyzing long-term trends in mean climatic conditions or by examining the effects of short-term climate variability. (Miyamoto & Hackmann, 2025). Including temperature alongside precipitation data enables the Standardized Precipitation Evapotranspiration Index (SPEI) to better capture the role of evapotranspiration in drought dynamics. Given the significant capabilities of both the Standardized Precipitation Index (SPI) and SPEI to detect and characterize drought events globally, their application provides valuable insights into drought behavior. Consequently, such analyses contribute to a more comprehensive understanding of drought impacts on crop productivity, particularly during critical stages of the growing season. This study seeks to examine the effect of drought indices on the yield of maize, rice, and millet in the Northwestern part of Nigeria.

2. Materials and Methods

2.1. Study area

The Northwestern part of Nigeria is situated between Latitudes 9° 0 ′ 00 ″ and 13° 49 ′ 30 ″ North of the Equator and Longitudes 3° 45 ′ 00 ″ and 10° 20 ′ 00 ″ East of the Greenwich Meridian. It shares borders with the Republic of Niger to the North and the Republic of Benin to the West, around Kebbi

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State (Figure 1). It is the most populous part of Nigeria, accounting for 25.75 percent of the Nigerian population. It is the third-largest region, in terms of geographical coverage, with an estimated area of 216,065 square kilometers (National Population Commission (NPC), 2006). Northwestern Nigeria is traditionally renowned for agriculture and aquaculture, which remain the main livelihoods of about 80% of the region's inhabitants. The states of Kaduna, Kano, Jigawa (Dutse), Katsina, Sokoto, and Kebbi have been major producers of food crops such as cereals, rice, maize, millet, and other staples, while vegetables such as onion, pepper, and watermelon. Because of the increasing cases of banditry, partly induced by drought, most farmers have relocated to other parts of Nigeria. (NAERLS, 2021).

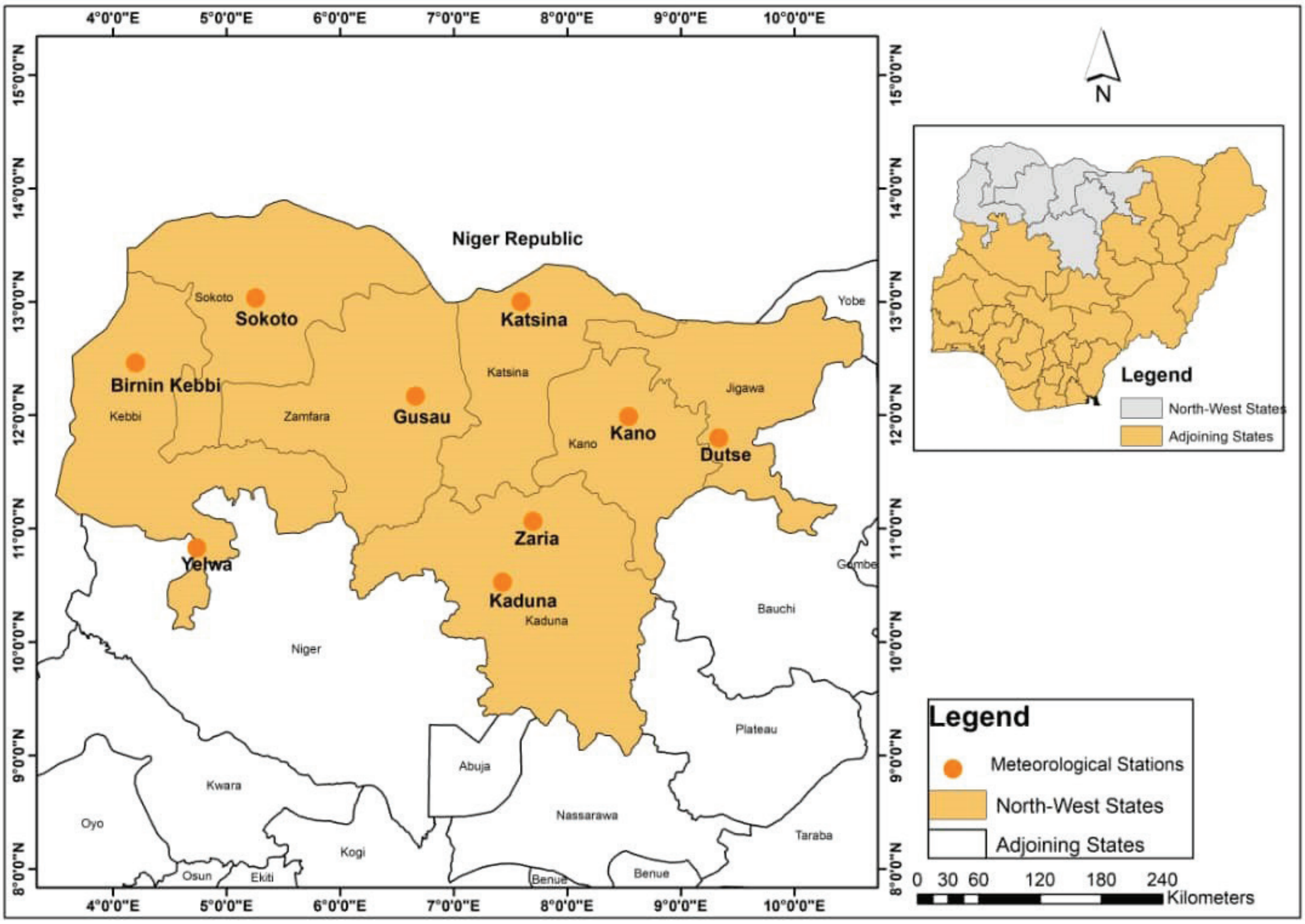

Figure 1: Study area

2.2. Climate

Northwestern Nigeria technically falls under Koppen's A_w classification, a hot, dry climate with no precipitation in the cold season and a mean annual temperature of 28 °C. However, in December and January, the night and early-morning temperatures could be well below 20°C. The average Maximum temperature ranges between 32 °C and 35 °C across the study area. The study area, in its southern parts, is situated in a dry sub-humid zone with an annual rainfall of over 1,000mm, while its northern part is semi-arid with an annual rainfall range of between 600 and 800mm. The northern part is arid with an annual rainfall of between 400mm and 600mm; this confirms that the study area has a dry climate. (Abdullahi and Ismail, 2019). Rainfall in the area is concentrated only from June to September, sometimes extending into October in the Southern parts, during which the humidity exceeds 60%. Rainfall in the study area is characterized by a few extremely high and torrential episodes. (Umar and Ismaila, 2017). The nethermost part of northwestern Nigeria's seasonal rainfall regime is more important than the annual total and a major controlling factor in the calendar of agricultural activities.(Li, et al., 2021).

2.3. Data collection

Six synoptic stations across Kebbi, Zamfara, Kano, Katsina, Sokoto, and Kaduna States were selected for this study. The selection criteria were based on the availability of long-term, consistent records of rainfall and temperature, as well as the stations' location within drought-prone areas. Additional spatial coverage was also considered. Monthly rainfall and temperature data spanning 42 years (1980–2021) were obtained from the archives of the Nigerian Meteorological Agency (NiMet). These data provided the basis for assessing climatic variability and drought conditions in the study area. Crop yield data for rice, maize, and millet were sourced for the period 2009–2021. Long-term time-series data on crop yields (1980–2021) were not readily available, which necessitated the use of secondary data from the National Agricultural Extension and Research Liaison Service (NAERLS). Consequently, the analysis of crop yield response to drought indices was limited to the period for which reliable agricultural data were accessible.

2.4. Standardized Precipitation Index (SPI)

Monthly rainfall was used for SPI analysis. The SPI compares precipitation over a specific period with the same period's total precipitation across all years in the historical record. (Alamgir et al., 2015). It is an easily calculated, flexible, and universal index that requires only precipitation data, which are the main reasons for its wide applicability in various drought-related applications worldwide. Several scholars have used the SPI for meteorological drought. (Abdulrahim et al., 2016; Chunming, 2010; Diani et al., 2019; Guenang & Kamga, 2014). Although it is primarily considered a meteorological drought index, it has also been used in many studies on hydrological and agricultural drought. (Tigkas et al., 2019). Positive SPI values indicate greater than median precipitation, and negative values indicate less than median precipitation. (Tigkas, et al 2015). It also allows the user to confidently compare historical and current droughts across different climatic and geographic locations when assessing the rarity or frequency of a given drought event (WMO, 2012). SPI equation is written below:

$$\textit{SPI Formula: } \frac{xi - x}{\partial} \tag{1}$$

Where,

x = the mean annual rainfall; xi = the annual rainfall at any year. ∂ = the standard variation

2.5. Standardized Precipitation Evapotranspiration Index (SPEI)

Monthly minimum and maximum temperatures collected from the Nigerian Meteorological Agency were used for SPEI analysis. A relatively new drought index, developed by Vicente-Serrano et al. (2010). SPEI uses the SPIs but includes a temperature component, allowing the index to account for the effect of temperature on drought development through a basic water balance calculation (Svoboda & Fuchs, 2016). SPEI has an intensity scale in which both positive and negative values are calculated, identifying wet and dry events. It can be calculated for time steps as short as 1 month and as long as 48 months. The input parameters are monthly precipitation, minimum temperature, and maximum temperature data. Including temperature alongside precipitation data allows SPEI to account for its impact on drought. The output is applicable across all climate regimes, with results comparable because they are standardized (Svoboda & Fuchs, 2016). SPEI = P- PET, where monthly PET is calculated using Hargreaves' method (1985). The method requires monthly temperature and precipitation. The equation is written below:

$$\textit{SPEI Formula: } di = pi - PET \tag{2}$$

Where,

di = difference of precipitation,

pi = a precipitation,

PET = potential evapotranspiration for a month.

2.6. Correlation and regression analysis

Crop production is highly dependent on weather parameters. The purpose of the correlation is to examine the relationship between drought indices and crop yield. Variability in meteorological parameters affects crop production and productivity (Bhattacharyya et al., 2021). Crops grown during the seasons were considered for regression, including maize, rice, and millet. Seasonal crop calendars remain a vital tool for the Nigerian agricultural sector, enabling farmers to synchronize planting and harvesting with ecological realities by optimizing yields, reducing losses, and strengthening food security. Figure 2 presents the main crops cultivated, which are maize, rice, groundnut, cowpea, millet, sorghum, soybean, and vegetables during the growing season, with the expected duration from planting to harvesting period in the study area. A multiple regression analysis was conducted to assess the effects of drought indices on crop yield. The independent variables are SPEI and SPI, and the dependent variable is crop yield. The stepwise regression method was used to obtain the desired equations using Minitab Statistical Package version 18. To assess model accuracy and predictive performance, three statistical metrics were used: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). These measures are widely recognized. Their application in this study is consistent with previous research, as demonstrated in studies by Mahmood et al. (2019), Olanrewaju & Shitu (2021), and Wichitarapongsakun et al. (2016), where similar metrics were used to evaluate model reliability and forecasting precision.

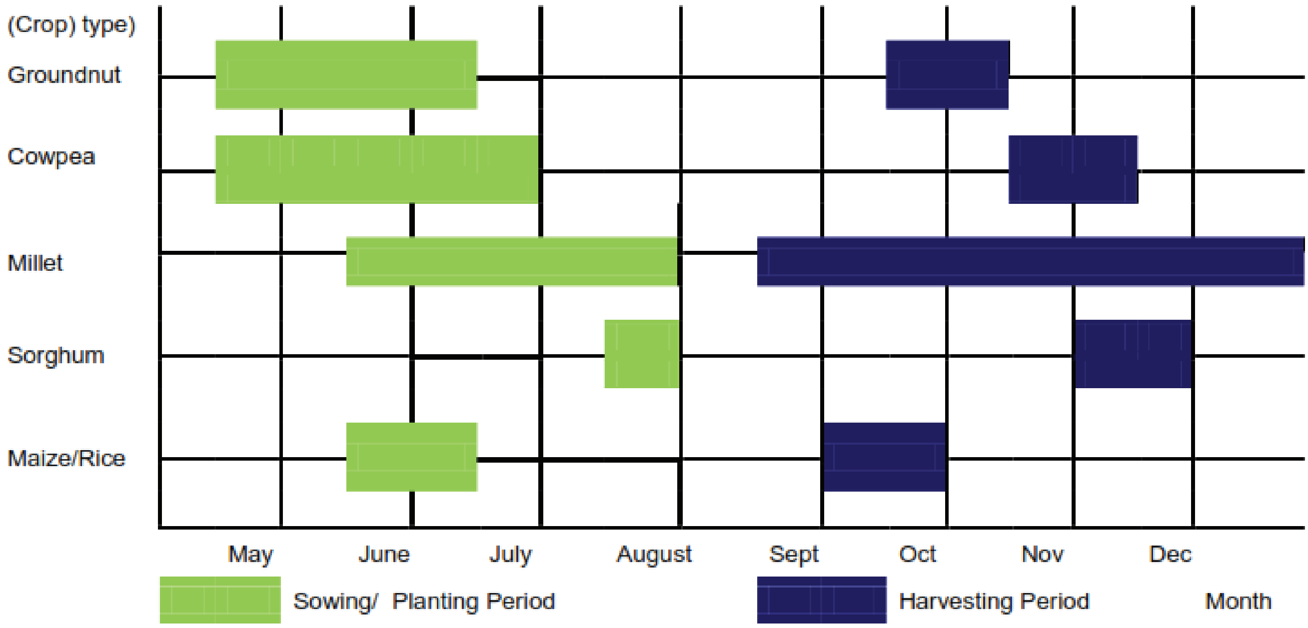

Figure 2: Crop calendar (Ndamani & Watanabe, 2015)

3. Results and Discussion

3.1. Regression analysis

To determine the effect of meteorological drought on crops, SPI, SPI, and estimated crop yield per hectare were used in a regression analysis. Findings revealed that in Kaduna, the R^2 values are 73.3% (SPI) and 80.3% (SPEI), indicating that more than 73.3% and 80.3% of the yield can be explained or predicted by these variables. Crop yield is significantly influenced by drought indices in Kaduna. For Jigawa, R2 is 66.65% (SPI) and 56.1% (SPEI), indicating that 66.6% and 56.1%, respectively. The yield is explained by these variables. The result indicates that rainfall and temperature positively influenced crop yield. This is because there are major inputs determining drought. These findings are consistent with (Bhattacharyya et al., 2021) who reported that crop production is highly sensitive to rainfall characteristics—particularly onset timing and the length of the growing period, as well as temperature variability. Regression results for rice, maize, and millet in Sokoto indicate that SPI and SPEI explain only 7.7% and 6.5% of yield variability, respectively, suggesting limited predictive capacity of these indices in isolation. The observed decline in average yields may therefore be attributed not only to drought conditions but also to other influencing factors, including soil texture, fertilizer application levels, pest infestations, diseases, and weed pressure.

The variation observed in the results of the multiple regression across locations is due to many factors. First, Kaduna and some parts of Kebbi are situated

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in the Guinea Savanna agro-ecological zone, whereas Jigawa, Zamfara, Kano, and Katsina are in the Sudan and Sahel Savanna agro-ecological zones. Gadedjisso-Tossou et al. (2021) supported this conclusion. They reported that crop development is expected to differ across agro-ecological zones. In addition, edaphic conditions vary across agro-ecological zones. Also, the availability of agricultural inputs such as fertilizer, labor, and seed varieties, which depend on farmers' socioeconomic characteristics, will also contribute to output. Moreover, in a related study, AbdulKadir et al. (2013), the appraisal of the eco-climatic characteristics in Northern Nigeria confirmed that the dynamics in the eco-climatic parameters, moisture effectiveness zone, is fundamental to the identification of the current state of the environment in Northern Nigeria.

Table 1: Summary of multiple regression equation and percentage of explanation

States	Indices	Regression Equation	R^2 (%)	Adjusted R^2
Jigawa	SPI	Y= -1.28 + 0.430 RICE + 0.22 Maize + 0.339 Milet	66.6	55.4
	SPEI	Y= 0.70 - 0.242 RICE - 0.27 Maize + 0.206 Milet	56.1	41.6
Gusau	SPI	Y= 5.38 - 0.1463 RICE - 2.162 Maize - 1.746 Millet	30.5	7.4
	SPEI	Y= 8.51 - 0.232 RICE - 3.40 Maize - 2.77 Millet	6.0	0.0
Kaduna	SPI	Y= 0.79 - 1.201 RICE + 1.654 Maize + 1.033 Millet	73.4	66.2
	SPEI	Y= 6.33 - 1.084 RICE + 3.870 Maize + 2.095 Millet	80.3	74.9
Kano	SPI	Y= 0.071 - 0.106 RICE + 0.226 Maize - 0.315 Millet	36.6	19.3
	SPEI	Y= 1.38 - 0.445 RICE + 0.134 Maize - 0.469 Millet	56.7	44.9
Kastina	SPI	Y= 0.817 - 0.798 RICE + 1.42 Maize - 1.64 Millet	15.9	0.0
	SPEI	Y= 0.701 - 1.258 RICE + 1.480 Maize - 0.67 Millet	37.5	16.6
Sokoto	SPI	Y= 1.55 + 1.11 RICE - 0.27 Maize + 0.27 Millet	7.7	0.0
	SPEI	Y= -1.58 + 0. 77 RICE - 0. 75 Maize + 1.05 Millet	6.5	0.0
Kebbi	SPI	Y= 0.41 + 0.010 RICE + 0.980 Maize - 1.06 Millet	21.7	0.0
	SPEI	Y= 4.40 - 1.85 RICE - 0.338 Maize - 0.09 Millet	15.9	0.0

Note: Yields are for Rice, Maize, and Millet. Y represents SPI and SPEI.

3.2. Modeling the relationship between crop yield and drought indices using regression techniques

According to Table 2, the model explains 52.4% of the total variation in maize yield in Kaduna State, as reflected by the coefficient of determination (R^2). After adjusting for the number of predictors in the stepwise regression model, the adjusted R^2 decreased slightly to 48.1%, indicating a moderate level of explanatory power and suggesting a moderate relationship between drought conditions and maize yield. The results demonstrate that both SPI and SPEI account for 11.6% and 10.6% of the variance in maize in Kastina and Kebbi, respectively. It is clear that these two indices jointly account for the lowest variance in rice production across the state, with 0% in Katsina. This may be attributed to the fact that rice is cultivated under conditions where water is available for a substantial portion of the growing season; consequently, drought may not serve as a primary determinant of yield variability. The adjusted R^2 measures the proportion of explained variation relative to the total variation and helps identify non-significant explanations. Based on this, it can be inferred that a relatively meaningful explanation was observed in Kaduna, with a value of 0.48. This indicates that the model explains more of the variance in maize in Kaduna than in other crops. The relatively low Mean Squared Error (MSE) values further support the model's adequacy, with a notably low value of 0.040 for maize in Jigawa State. In contrast, moderately higher MSE values were observed for millet in Zamfara (0.632) and Sokoto (0.613). Furthermore, Sokoto State recorded the highest MSE value (0.907) for maize, indicating comparatively lower predictive accuracy of the model in that context. The Root Mean Squared Error (RMSE) is another key measure of model fit, as it accounts for unexplained variation. The lower RMSE values recorded in Jigawa (0.201) and Kaduna (0.250) indicate a smaller deviation between dependent variables, maize, rice, and millet, and suggest a better model fit. This further confirms the influence of drought indices in the study area. In a related study, Raha & Gayen (2020) reported that areas with extreme to severe drought exhibited higher RMSE values.

Mean Absolute Percentage Error (MAPE) measures the average magnitude of error produced by the model. The findings revealed the three highest MAPEs across states as follows: Zamfara 83.968% (millet), 76.616% (maize), and 173.144% (millet) recorded in Sokoto, while the lowest values were recorded in Jigawa 9.491% (maize), Kaduna 7.741% (maize), and Kebbi 9.460% in (rice). Higher values of the Mean Absolute Percentage Error (MAPE) suggest that the model may have inadequately captured critical crop growth stages, which also confirms the nature of the data used. Conversely, lower MAPE values indicate improved predictive accuracy of the Standardized Precipitation Index (SPI) and Standardized Precipitation Evapotranspiration Index (SPEI) for maize and rice in Jigawa, Kaduna, and Kebbi States, whereas higher MAPE values reflect reduced model performance and less reliable predictions. "Recent studies (Ng et al., 2023) assessed the performances of the predicting models using root-mean-square error (RMSE), mean absolute error (MAE), and Mean Absolute Percentage Error (MAPE). The accuracy of drought forecasting was associated with a lower MAPE, and SPI indices were used as the standard model for evaluating drought accuracy. A critical look revealed that the majority show positive autocorrelation across states; this is because the values are less than 2, except in Jigawa (2.094), Kaduna (2.52), and 2.089, which indicate negative autocorrelation, respectively. This finding further confirms that the weather requirements of the dependent variables used differ remarkably. The greater the F-values, the more accurate the regression. Kaduna has the highest F-value, with 12.112, while the lowest was zero, recorded in Kano. This could imply that the regression fits Kaduna better than other states.

Table 2: Summary of the goodness of fit for the regression model between crop yield and drought indices

States	Crops	R^2	Adjusted R^2	F values	MSE	RMSE	MAPE
Jigawa	Rice	0.023	-0.065	0.263	0.566	0.753	55.395
	Maize	0.050	-0.037	0.573	0.040	0.201	9.491
	Millet	0.038	-0.050	0.430	0.060	0.245	21.320
Gusau	Rice	0.017	-0.072	0.189	0.580	0.223	36.757
	Maize	0.050	-0.036	0.580	0.079	0.282	17.038
	Millet	0.020	-0.069	0.223	0.632	0.795	83.968
Kaduna	Rice	0.030	-0.059	0.335	0.090	0.299	8.037
	Maize	0.524	0.481	12.112	0.063	0.250	7.741
	Millet	0.064	-0.021	0.752	0.092	0.303	37.210
Kano	Rice	0.000	-0.091	0.000	0.344	0.586	19.417
	Maize	0.080	-0.003	0.961	0.094	0.306	9.327
	Millet	0.098	0.016	1.201	0.281	0.530	53.331
Kastina	Rice	0.003	0.003	0.326	0.251	0.501	25.118
	Maize	0.116	0.116	0.293	0.179	0.423	27.277
	Millet	0.078	0.078	0.625	0.044	0.210	25.104
Sokoto	Rice	0.108	0.027	1.337	0.127	0.357	19.479
	Maize	0.022	-0.067	0.252	0.907	0.953	173.144
	Millet	0.110	0.029	1.353	0.613	0.783	76.616
Kebbi	Rice	0.012	-0.077	0.138	0.094	0.306	9.460
	Maize	0.106	0.025	1.304	0.280	0.529	34.999
	Millet	0.032	-0.056	0.360	0.070	0.264	33.498

3.3. Assessment of the linear relationship between drought indices and crop yield

Correlation analysis measures the strength and direction of the linear relationship between the independent and dependent variables. Table 3 shows the estimated crop yield distribution observed on annual production for each of the major rainfed crops cultivated during the rainy season. These are rice, maize, and millet. The analysis of correlation coefficients revealed that the Standardized Precipitation Index (SPI) exhibited both positive and negative relationships with the annual yield of the studied crops, with comparatively stronger associations than those observed for the Standardized Precipitation Evapotranspiration Index (SPEI) in some cases. Notably, strong positive relationships were observed in Kaduna State between SPEI and maize yield (r = 0.77), SPI and maize yield (r = 0.647), and SPEI and rice yield (r = 0.66). In contrast, a strong negative correlation was identified in Kano State between SPEI and millet yield (r = -0.684), indicating an inverse relationship between drought conditions and millet production in that location. The analysis implied that as the number of positive SPEI values increased, crop yields also increased, except for SPEI and millet, for which yields decreased. The correlation statistics between SPEI and Rice in Zamfara showed a negative correlation (r = -0.43), suggesting a weak relationship. As the SPEI value increases, rice yield decreases. This result is expected, given that cultivating rice requires more water. In a related study, Elagib (2013) reported a strong positive correlation between the Standardized Precipitation Index (SPI) and crop yield during the early to mid-growing season in the semi-arid area of Sudan.

However, the correlation coefficients may not be statistically significant; it should be noted that the correlation values between drought indices and crop yield indicate that climate variables such as rainfall and temperature are sensitive to agricultural production. Previous studies confirmed that agriculture is perhaps the most weather-sensitive of all man's economic activities (Ayoade, 1993). Report by Agricultural Extension and Research Liaison Services (NAERLS, 2021) in an assessment of the recent decrease in land cultivated and yield witnessed in some states could be traced to incessant kidnapping and bandit activities that make it difficult for farmers to move freely to perform agricultural activities, especially in Zamfara, Katsina, Niger, Sokoto, and Kebbi. Some farmers have outrightly left farming, while many have relocated to Internally Displaced People's (IDP) camps for safety and humanitarian support. In view of the foregoing, one can infer that the total devoted to wet-season farming also played a significant role in annual crop yield. Previous studies (Adepoju et al., 2022) reported that drought is a key abiotic stress affecting maize yield and production in Sub-Saharan Africa, contributing between 44% to 58% grain yield decline in West and Central Africa. The negative relationship observed in SPEI (Table 3) further confirmed the impact of temperature and potential evaporation on the index's use. The related study conducted in America (Hatfield & Prueger, 2015) showed that the major impact of warmer temperatures was during the reproductive stage of development, and in all cases, grain yield in maize was significantly reduced by as much as 80-90% from a normal temperature regime.

The results of the linear relationship between drought indices and crop yield (Figures 3, 4, 5, 6, 7, 8, and 9) clearly demonstrated a pattern of heterogeneous variance (non-constant variance) across SPI, SPEI, and crop yield. It should be noted that there is a relationship between the drought indices and crops, as adequately explained earlier in Table 2 above, except that the general pattern follows a linear trend. These could be a result of their responses to temperature and rainfall, which differ among crop species throughout their life cycle, particularly during stages of plant development, which is consistent with other findings (Gebremichael et al., 2014; Salack et al., 2015). It can also be seen that SPEI exhibits greater variation in many instances than SPI, which only quantifies precipitation deficit or surplus at different time scales. The results are in line with the studies of (Gadedjisso-Tossou et al., 2021), who assessed that the variation of rainfall and temperature has a significant effect on the cereal crop yields in Togo.

Table 3: Correlation between drought indices and crop yield

States	Variables	SPEI	SPI	RICE	Maize	Millet
Gusau	SPEI	**1.000**	0.453	-0.143	-0.185	0.085
	SPI	0.453	**1.000**	0.497	0.318	0.460
	RICE	-0.143	0.497	**1.000**	0.681	0.519
	Maize	-0.185	0.318	0.681	**1.000**	0.160
	Millet	0.085	0.460	0.519	0.160	**1.000**
Jigawa	SPEI	**1.000**	0.453	-0.278	0.191	-0.412
	SPI	0.453	**1.000**	0.386	0.243	-0.213
	RICE	-0.278	0.386	**1.000**	0.240	0.03*
	Maize	0.191	0.243	0.240	**1.000**	-0.871
	Millet	-0.412	-0.213	0.03*	-0.871	**1.000**
Kaduna	SPEI	**1.000**	0.702	-0.088	0.774	0.314
	SPI	0.702	**1.000**	-0.328	0.647	0.287
	RICE	-0.088	-0.328	**1.000**	0.065	0.129
	Maize	0.774	0.647	0.065	**1.000**	-0.047
	Millet	0.314	0.287	0.129	-0.047	**1.000**
Kano	SPEI	**1.000**	0.852	-0.661	-0.224	-0.684
	SPI	0.852	**1.000**	-0.385	0.023	-0.568
	RICE	-0.661	-0.385	**1.000**	0.502	0.628
	Maize	-0.224	0.023*	0.502	**1.000**	0.186
	Millet	-0.684	-0.568	0.628	0.186	**1.000**
Kastina	SPEI	**1.000**	0.642	-0.284	0.107	0.152
	SPI	0.642	**1.000**	-0.074	0.087	-0.064
	RICE	-0.284	-0.074	**1.000**	0.778	0.414
	Maize	0.107	0.087	0.778	**1.000**	0.750
	Millet	0.152	-0.064	0.414	0.750	**1.000**
Sokoto	SPEI	**1.000**	-0.381	0.156	0.180	0.212
	SPI	-0.381	**1.000**	0.272	0.161	0.132
	RICE	0.156	0.272	**1.000**	0.625	0.459
	Maize	0.180	0.161	0.625	**1.000**	0.937
	Millet	0.212	0.132	0.459	0.937	**1.000**
Kebbi	SPEI	**1.000**	0.007*	-0.470	-0.229	-0.117
	SPI	0.007*	**1.000**	0.096	0.401	0.086
	RICE	-0.470	0.096	**1.000**	0.152	0.003*
	Maize	-0.229	0.401	0.152	**1.000**	0.661
	Millet	-0.117	0.086	0.003*	0.661	**1.000**

**95% confidence level, *Significant 0.05*

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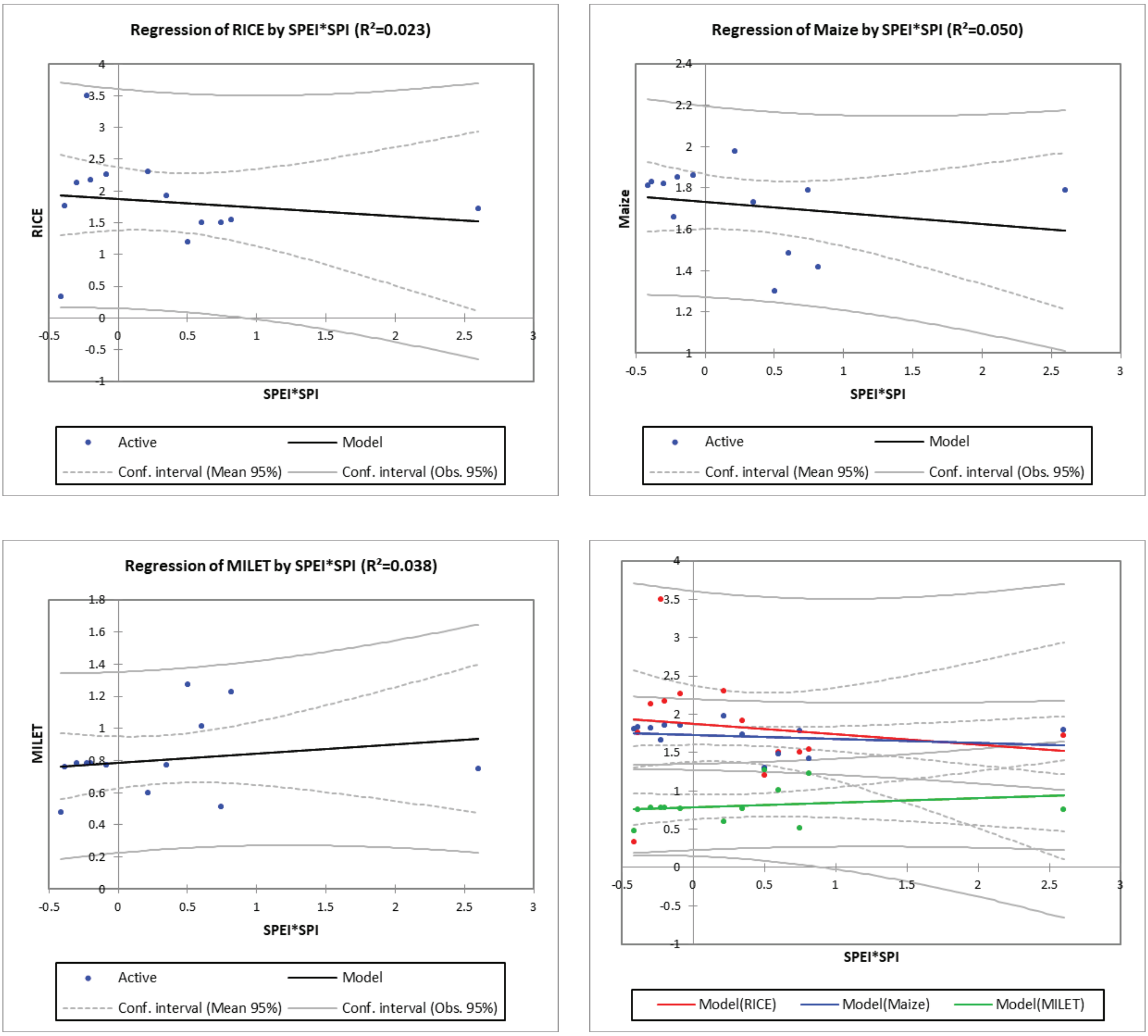

Figure 3: Linear relationship between drought indices and crop yield in Jigawa

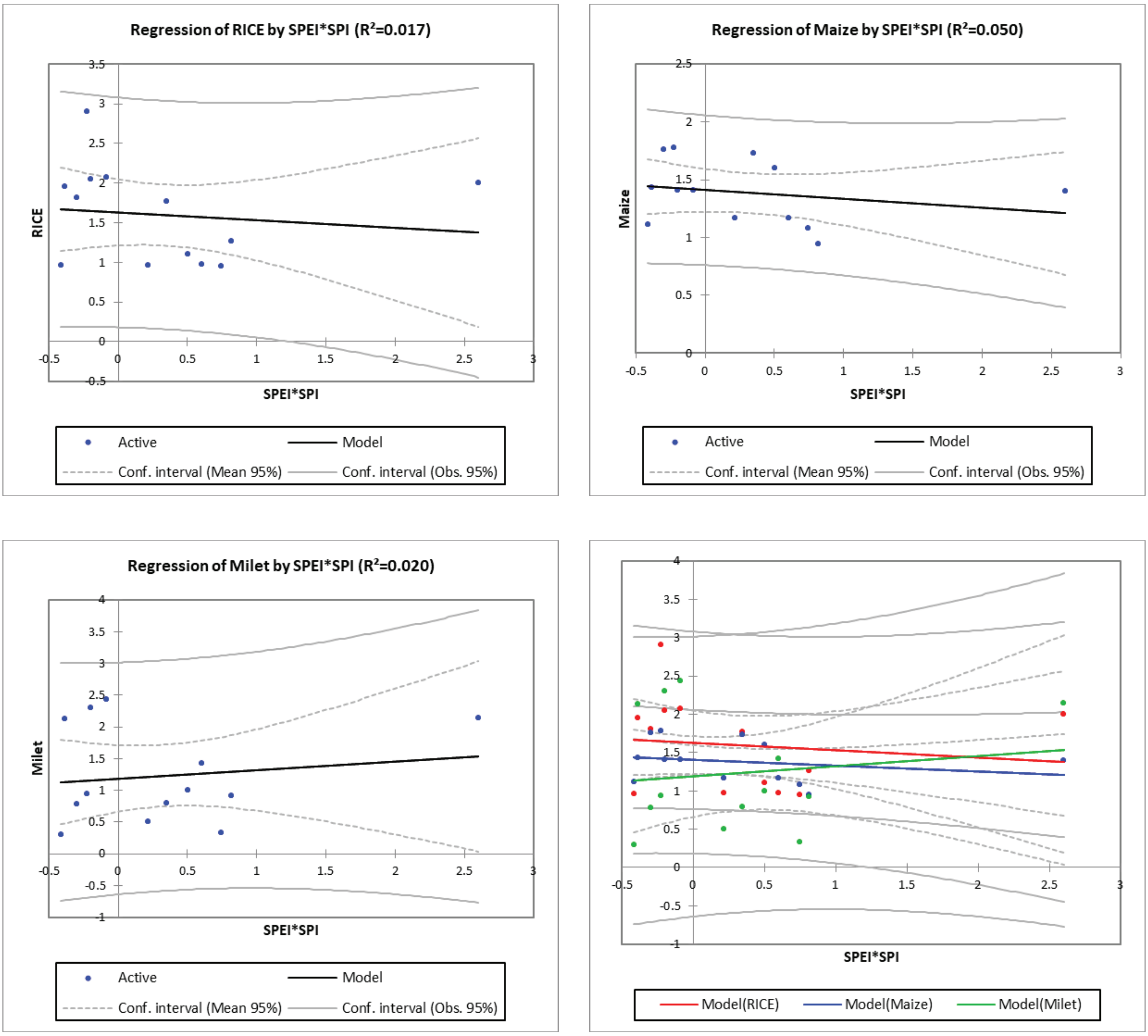

Figure 4: Linear relationship between drought indices and crop yield in Zamfara

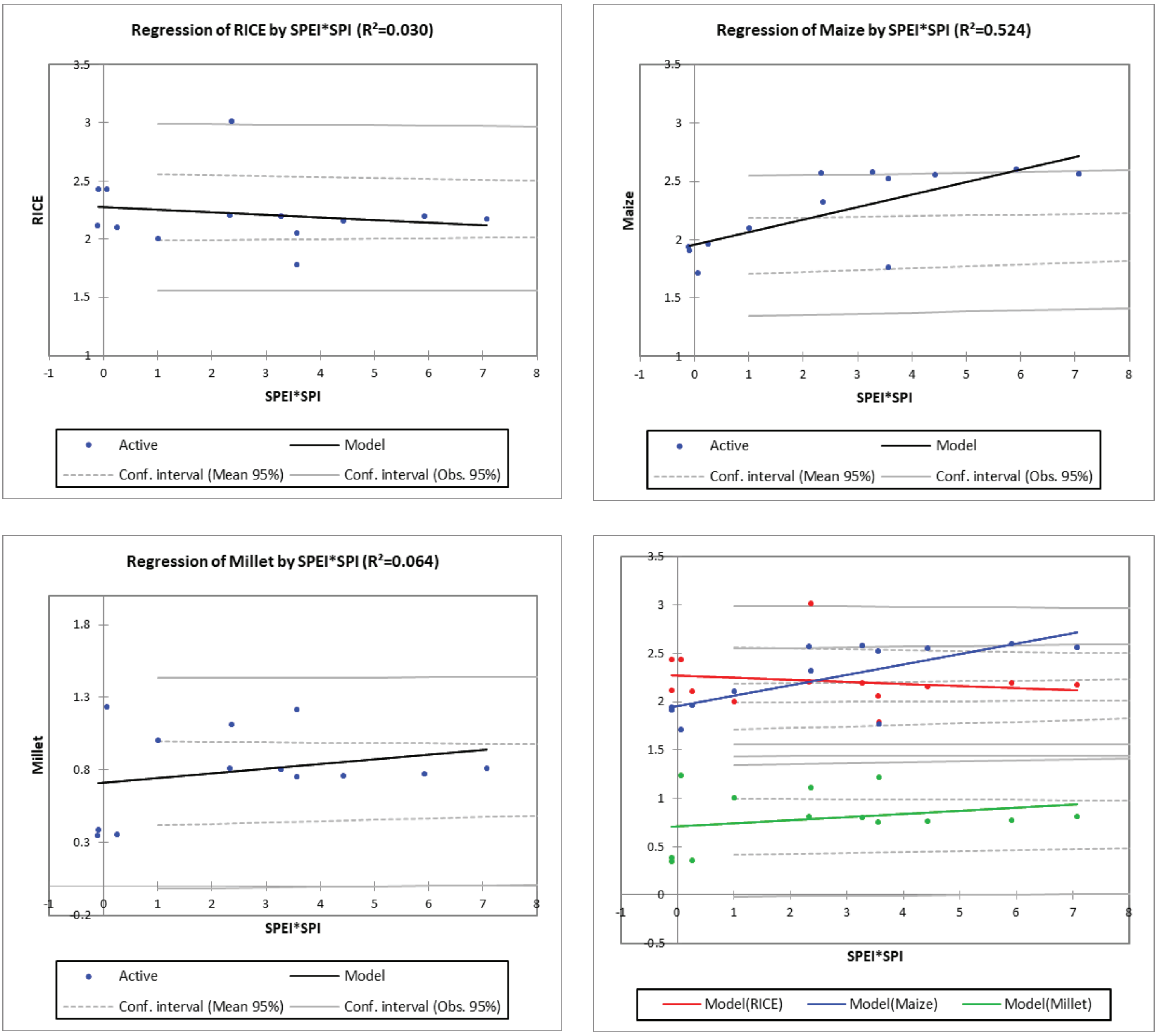

Figure 5: Linear relationship between drought indices and crop yield in Kaduna

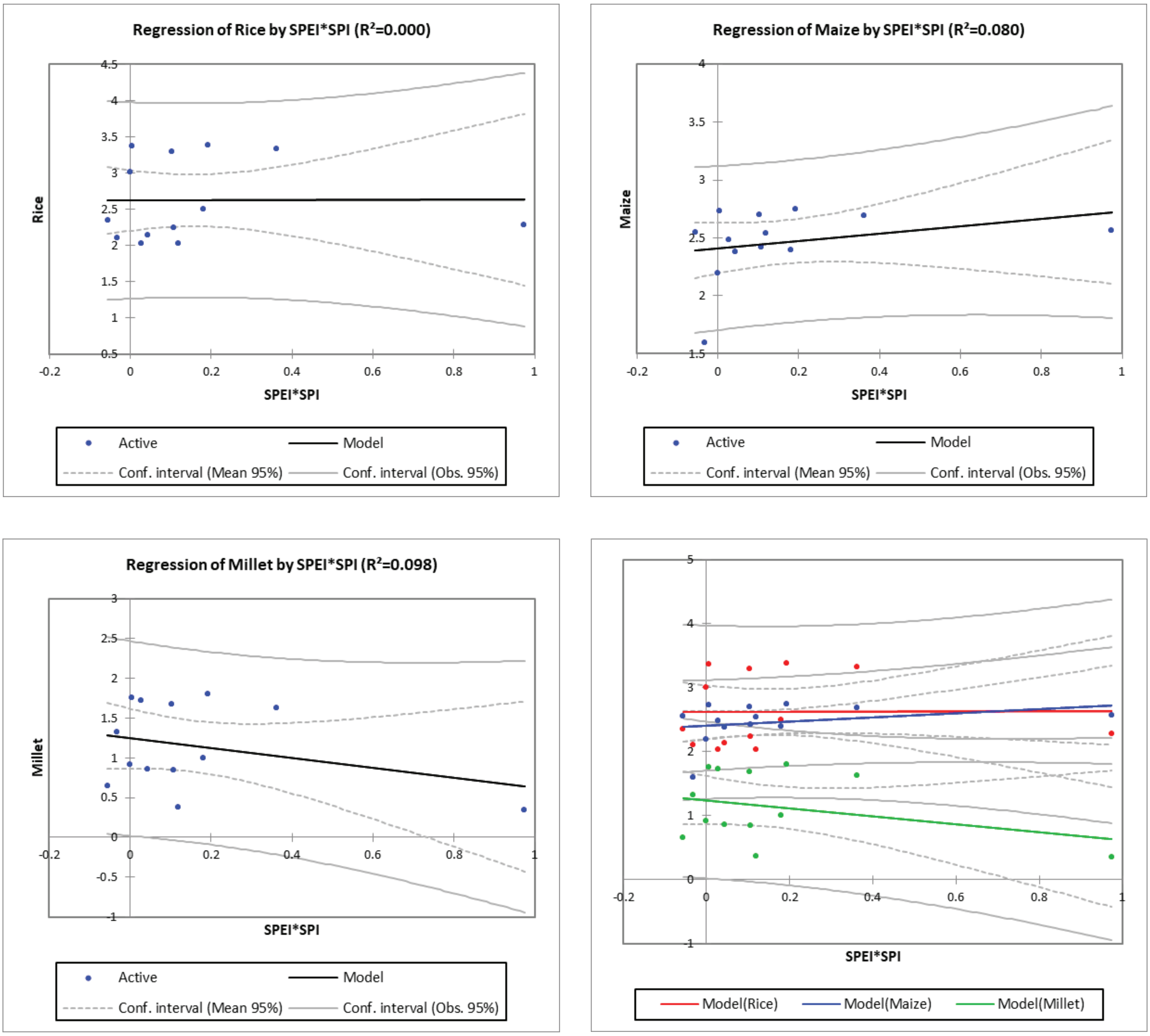

Figure 6: Linear relationship between drought indices and crop yield in Kano

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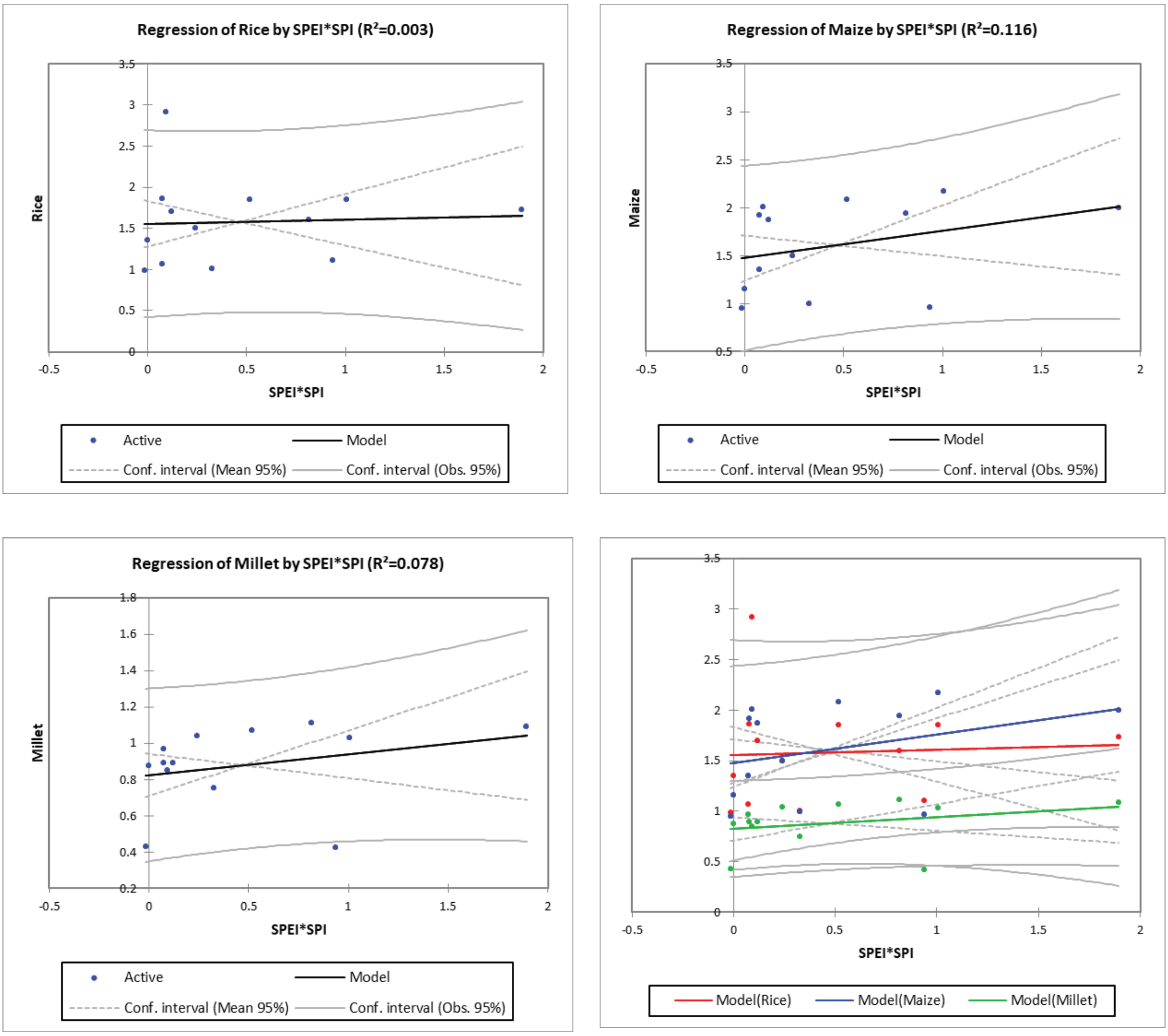

Figure 7: Linear relationship between drought indices and crop yield in Kastina

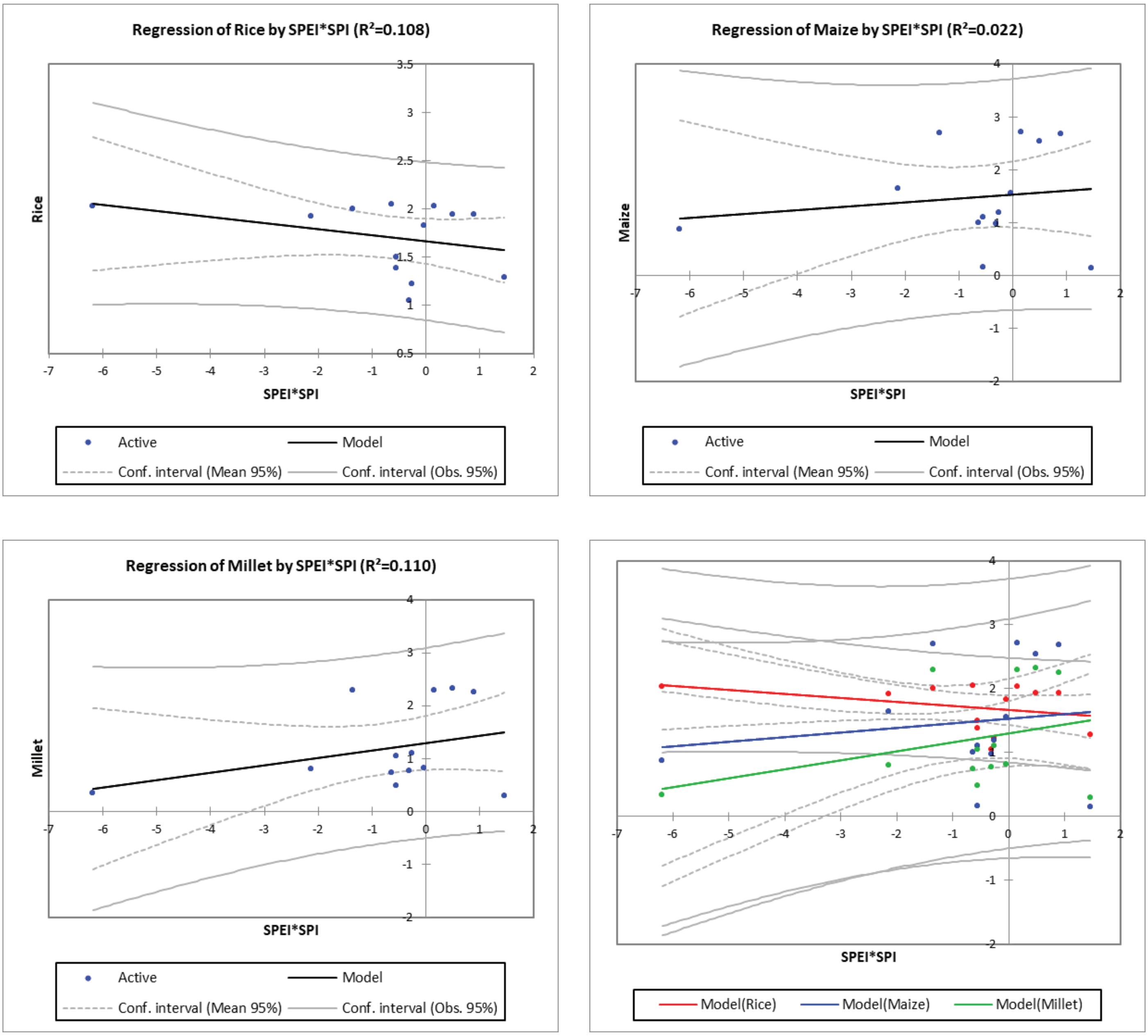

Figure 8: linear relationship between drought indices and crop yield in Sokoto

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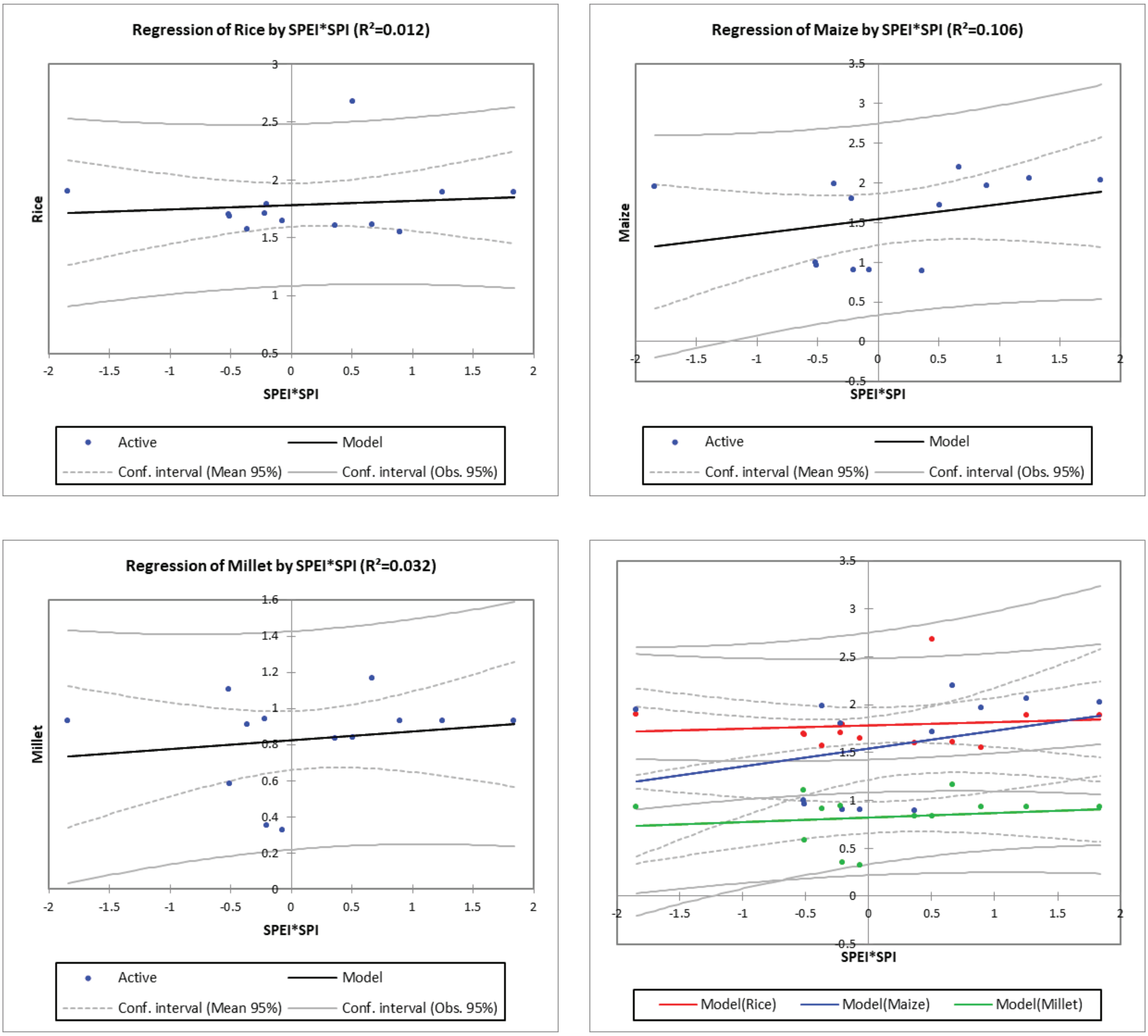

Figure 9: Relationship between drought indices and crop yield in Kebbi

4. Conclusion

The study demonstrates the relationship between meteorological droughts and the yield of rice, maize, and millet in Northwestern Nigeria. This was performed by analyzing drought characteristics using SPI and SPEI indices and correlating them with crop yield. The drought indices presented herein allow the estimation of the frequency of occurrence of the different drought severity classes. It was revealed that correlations between drought indices and crop yield showed both negative and positive relationships. The impact of drought indices on crop yields varied significantly by state and crop. The SPEI appeared to be significant and contributed to the increase in the yields of all selected crops compared with SPI.

It has been found that the SPEI could provide a useful tool for predicting crop yield at an earlier stage in the crop calendar than the SPI. Using the June-September major growing period of the study area. The results of this research enhance our understanding of the impacts of drought indices on crops cultivated during the growing season. Examination of the regression functions of SPI and SPEI for rice, maize, and millet revealed that SPEI accounted for more variation. It can be concluded that a combination of temperature and rainfall plays a significant role in crop yields in the study area.

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