CEEPA Discussion Paper No.61
ISBN 1-920160-61-6, April 2015

EFFECT OF WEATHER EXTREMES ON CROP YELDS WITH IMPLICATIONS FOR CROP INSURANCE IN NIGERIA

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[1] This research work was carried out with the aid of a grant from the Centre for Environmental Economics and Policy in Africa (CEEPA) (www.ceepa.co.za), financed by the Swedish Development Cooperation Agency (SIDA). I gratefully acknowledge the technical assistance and useful suggestions of Professors Rashid Hassan, David Starrett, Marty Luckert, Tekie Alemu, Joe Cook, Margaret Chitiga, Edwin Muchapondwa, Wisdom Akpalu and others. I am very grateful to National Meteorological Agency, Lagos Nigeria for access to daily climate data on Nigeria and Prof Wolfram Schlenker for assisting me with the stata do-file. I am equally indebted to Mrs. Dalene Duplesis for all secretariat assistance and other researchers that contributed to the improvement of this study at various CEEPA workshops. The comments of the reviewers are equally appreciated. All errors however should be considered to be mine.

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Abstract

This study seeks to (1) analyze how extreme weather conditions affect crop yield and risk in Nigeria, and (2) assess the potential implications of weather extremes on the nation's crop insurance portfolio. In the study, a panel of Nigerian state-level crop yields is paired with a fine-scale weather data set that includes distribution of temperatures and precipitation between the minimum and maximum across all days within the growing season for selected crops. Weather data are examined from January 1, 1991 to December 31, 2012. The results show that a high damage to cassava, cotton and maize is evident by the strong and negative coefficient of Harmful Degree Days (HDD). For sorghum and rice, an exposure to heat range that is expected to have positive effects on the yield is already showing negative influence. Given the above results coupled with several problems associated with National Agricultural Insurance Corporation (NAIC) such as little access by farmers, high information asymmetric and transaction costs, crop insurance based on indices from Nigeria Meteorological Agency (NIMET) could fill the gap.

Acronyms

IPCC	Inter-governmental Panel on Climate Change
NAIC	National Agricultural Insurance Scheme
NIMET	Nigerian Meteorological Agency
USDA	United State Development Agency
FMARD	Federal Ministry of Agriculture and Rural Development
ATA	Agricultural Transformation Agency
GDD	Growing Degree Day
HDD	Harmful Degree Day
VPD	Vapour Pressure Deficit
RMSE	Root Mean Square Error
WIIA	Weather Index Insurance for Agriculture

1.0 Introduction

Agriculture is inherently risky. Farmers usually lack knowledge of the precise output at the time of their production and input decisions, because agriculture in general has a relatively long production cycle and is affected by a large number of endogenous or exogenous uncertainty factors. The prevailing climatic conditions, for instance, are important sources of uncertainty. Climatic factors such as temperature, rainfall or sunlight are characterized by inter-annual variability, part of which can be explained by gradual shifts in mean conditions, but another part is constituted by seemingly random fluctuations. The overall direction and magnitude of the inter-annual variations are beyond farmers' control as well as their predictive capabilities. As a result, climate is not only an important determinant of the general suitability of any given region for agricultural production, but also a source of substantial production risk, causing unexpected variability of output.

In both the developing and developed worlds, extreme weather events and climatic anomalies can have serious effects on agriculture. Weather extremes and climate anomalies can affect yields and disease patterns. For instance, when droughts are followed by intense rains, they may increase the potential for flooding, thereby creating conditions that favour fungal infestations of leaves, roots, and tuber crops. Sequential extremes, along with altered timing of seasons, may also decouple long-evolved relationships among species (e.g., predator/prey) essential for controlling pests and pathogens as well as populations of plant pollinators (Epstein and Chilwenhee, 1994). Therefore, an objective assessment of the potential impacts of climate on agriculture should be based, not only on the mean values of expected climatic parameters, but also on the probability, frequency, and severity of possible extreme events. Hence when user-focused weather and climate information are readily available and used wisely by farmers and agricultural insurance corporations, losses resulting from adverse weather and climatic conditions can be minimized.

In recent decades in Nigeria, major advances in short term and seasonal weather forecasting, as well as in long term climate modeling, are available for early warnings and advisories. These have caused an increasing emphasis on management of the risk to agriculture from extreme weather event and anomalies in climate conditions. Each year, a large amount of government spending in Nigeria is devoted to two major programmes that help farmers manage risk. The programmes are: subsidized premiums for agricultural risk-reducing insurance policies and frequent ad-hoc disaster payments to reimburse farmers after occurrence of natural disasters. It is expected that these costs will continue to increase because of climate change and increased occurrences of extreme weather events unless proper reform is put in place. Fundamental to such a reform will be an adequate knowledge of the effects of weather extremes on yields of various crops grown in the nation, particularly those covered by the nation's Agricultural Transformation Agenda (ATA). The main objectives of this paper are to:

(1) estimate the effect of extreme weather on yields for the following major Nigerian staple crops: cassava, cotton, maize, rice, and sorghum.
(2) Draw out potential implications of yield decline due to extreme weather on the nation's crop insurance scheme

2.0 Literature Review

Traditionally, time series data have been used to assess the influence of year-to-year weather fluctuation on crop yields. Rosenzweig and Parry (1994) use calibrated crop-models to examine the effects of year-to-year weather fluctuation on crop yields and simulate farm adaptation options. Deschenes and Greenstone (2007) use a panel data set to estimate the relation between profits and climatic variables in the United States of America. The authors regress profits in a county on climatic variables using county fixed effects. Chalise and Ghimire (2013) utilize historical data on yield, temperature, and precipitation in three adjacent agricultural districts of Georgia to assess the impacts of temperature and precipitation on mean yield of peanut production. The study finds that all levels of temperature have positive impact on peanut yield. Similarly, precipitation has positive impact on yield but up to certain limit. Excessive precipitation has negative effect on peanut yield.

Schlenker and Robert 2006 employ a 55-year panel of crop yields in the United States paired with a weather data set that incorporates the distribution of temperatures between the minimum and maximum within each day and across all days in the growing season to estimate the impacts of climatic factors on crop yield. The study shows that yields increase as temperature increases until about 29◦C for corn and soybeans and 33◦C for cotton, but temperatures above these thresholds quickly become harmful. Soja and Soja examine which kind of extreme weather causes bad harvests for seven agricultural crop species in three regions of Austria. The data consisted of the area-based agro-statistical surveys and the monthly means of meteorological parameters from 1869 to 2003. The results show that milder winters will be especially advantageous if no extreme temperatures occur in February while dry weather in spring is especially disadvantageous for spring cereals. Dry, hot summers are unfavourable for sugar beet and corn and to a lesser extent for potato.

Robertson (2012) provides a detailed review of partial equilibrium modeling of the short term and localized effect of climate. The models are production or profit (Gay et.al, 2006; Schlenker and Robertson, 2006, 2008; Deschenes and Greenstone 2007), hedonic model (Mendelsohn and Reinsborough 2007, Mendelsohn 2009, Wang et.al, 2009, Ajetomobi et.al 2011) and simulation model (Rosenzweig and Parry, 1997; Felkner 2009). Robertson (2012) uses the production model to capture the marginal impact of temperatures modeled in three ways, namely, monthly average, GDD and SR. She specified the general model which takes the form shown in Equation 1, where the natural log of yields, y, for crop i in year t, is a function of temperature (TEMP) in ºC, total seasonal rainfall in mm (RAIN), a vector of district dummies, D, and a time trend, T. Climate variables and the district dummies are vectors.

$$\ln Y_{it} = \ln \alpha_i + \beta_{ikt} \ln TEMP_{kt} + \vartheta_{i\pi} RAIN_{\pi} + \gamma_{ij} D_j + \delta T_i + \varepsilon_i \tag{1}$$

She hypothesized that temperatures in the mid-30s (ºCelsius) have a different marginal impact than temperatures in the mid-20s (º Celsius). Luo (2011) provides a review of temperature thresholds for a range of crops. Such identification of temperature thresholds provides a basis for quantifying the probability of exceeding temperature thresholds which is a very important aspect of climate change risk assessment. He also reviews the effects of extreme temperatures on yield and yield components.

At present, little empirical evidence exists on crop yield variation in response to the alterations in climatic conditions in sub-Sahara Africa. Further, none of the previous studies assess the effects of major climatic factors (temperature and precipitation) on mean and variance of crop yield in Nigerian states despite regular newspapers' reports of weather-based disasters affecting crop yields.

3.0 Methodology

3.1 Econometric Model Specification

Following Robert et al; 2012, the analysis uses the traditional approach to estimating climate change impact by a quadratic model of weather fluctuation or growing degree days on crop yields using Ordinary Least Square (OLS) and various panel data estimators. In the approach, crop yield is specified as a function of weather inputs (temperature and precipitation). In real world situation, production function may have other factors such as labour, pesticides, and farm owners' adaptation to adverse weather shock. A lack of available data, however, does not allow inclusion of the variables in the model. As a result, the model was tested for omitted variable bias. In addition, location and time fixed effects are employed to control for regional differences in soil quality, and technological progress or other shocks across a given geography and time. The panel models rely on an assumption of no adaptation so as not to overestimate the impact of a negative shock.

The production function is shown in model 1

$$\text{Model 1: } \log(YD_{it}) = \beta_0 + \beta_1 Tave_{it} + \beta_2 Rain_{it} + \beta_3 Tave_{it}^2 + \beta_4 Rain_{it}^2 + \varepsilon_{it} \qquad (2)$$

Where YD_{it} is de-trended crop yield in Kg/hectare for state i in year t

$Tave_{it}$ is average daily temperature for state i at year t

$rain_{it}$ is cumulative daily rainfall of state i at year t

If Growing Degree Days (GDD) and Harmful GDD (HDD) are used instead of mean temperature, the equation becomes:

$$\text{Model 2: } \log(YD_{it}) = \alpha_0 + \alpha_1 Rain_{it} + \alpha_2 Rain_{it}^2 + \alpha_3 GDD + \alpha_4 HDD + \varepsilon_{it} \qquad (3)$$

In the third model, Vapour Pressure Density (VPD) is added to the second model

$$\text{Model 3 : } \log(YD_{it}) = \delta_0 + \delta_1 Rain_{it} + \delta_2 Rain_{it}^2 + \delta_3 GDD + \delta_4 HDD + \delta_5 VPD + \varepsilon_{it} \qquad (4)$$

GDD and HDD are growing degree days (8-32 degree Celsius) and harmful growing degree days (temperature greater than 34 degree Celsius) respectively

3.2 Description of the Dataset

This section describes the yield, and weather data (temperature and rainfall) l used in the analysis. The weather data in each state are matched up with the yield of each crop over the particular crop growing season.

3.2.1 Crop Yields

Annual crop yields for five major crops including maize, sorghum, cotton, rice and cassava were obtained from the official records of each state Agricultural Development Programme. These crops were selected because they constitute priority staple food commodities under the nation's Agricultural Transformation Agenda (ATA) action plan (FMARD 2013). The data are available for all states in the country from 1991 to 2012. The records include information on total production, land area, number of farmers growing each crop and the crop's market price. Each state-average yield is derived as total production divided by total harvested hectarage. In all, there exist 37 states with yearly observations for cassava, maize and rice, 12 for cotton and 21 for sorghum. Table 1 shows the highest and lowest individual yield observations, by crop, in the dataset.

Table 1: Average recorded lowest and highest yields and average (kg/ha) across producing states for selected crops, 1991-2012.

Crop	High yield (Kg/hectare)	Year	Low yield (Kg/hectare)	Year	Mean yield (Kg/hectare)
Cassava	43.503	1999	1.085	2001	10.678
Rice	17.083	2003	0.180	2001	1.861
Maize	7.995	1991	0.141	2009	1.885
Sorghum	4.111	2012	0.176	2012	1.242
Cotton	5.454	1998	0.189	2012	1.649

Source: Author's calculation

The Table shows that the highest yield (43.50 kg/ha) for cassava was observed in 1999 while the lowest yield (1.085 kg/ha) was observed in 2001. For Sorghum, both highest and lowest yields were recorded in 2012. The average yield by various states over the entire analysis period is shown in Appendix A, Table A1. The results show that Abia, Borno, Kebbi, Delta and Zamfara states has the highest yield for cassava, cotton, maize, rice and sorghum respectively. Following Robert et al 2012, the yield used as the dependent variable is defined as

$$YD = 100 \times (\log(Yield) - \log(Trend)) \quad (6)$$

Where YD is de-trended yield

They provide the following reasons as the basis for de-trending: (i) yields have trended up with technological advancement, (ii) trend explains a large portion of the overall variance, de-trending therefore will ensures that the R^2 only measures the effect of weather variables, and (iii) A log standardization correctly and parsimoniously accounts for relationship between yield and both the mean and variance of the trend variable. Graphical illustrations of the de-trended yield and other key variables as well as their pair-wise correlation are shown in Appendix A. Approximately, the pair-wise scatter plots of the variables for all the crops show linear associations, few outliers or nonlinear clumping of data. In essence, simple correlations should approximate the degree of dependence. For cassava, rice and maize, the relationship of the yield with each of the weather variable except rainfall is negative. In contrast, yield is negatively correlated with rainfall for cotton and positive for others. For Sorghum, the relationship is negative for GDD and VPD but positive for all others. Overall, VPD predicts yield for most of the crops than other variables.

3.2.2 The Growing Season

The growing seasons for the selected crops are shown in Table 2. The growing seasons vary, depending on whether the crop is grown in the northern or southern part of Nigeria. In addition, maize and rice have two growing seasons in the country. The growing seasons for the selected crops are determined by the major planting days and harvest days reported by USDA. The planting and harvesting days vary from Northern to Southern part of Nigeria. They also vary from year to year depending on weather severity. Therefore, the growing season included in the empirical analysis for each crop, cut across the two regions. The following major growing seasons were used in the analysis: Maize from March to October to cover both early and late maize seasons, sorghum from April to August since it is predominantly grown in the guinea and sahel savannah regions, cotton from June to February after the first year, rice from April to December and cassava from January to December.

Table 2: Calendar for Selected Crops

Agro-ecological zones	Crop	Planting period onset	Planting Period end	Planting rate	cropping cycle
Derived savannah	Maize	01/03	31/08	25-32	100-120 days
Humid forest	Maize	01/03	31/08	25-33	100-120 days
Northern guinean savannah	Maize	01/03	31/08	25-30	100-120 days
Derived savannah	Rice	01/04	31/05	65	6-8 months
Northern guinean savannah	Rice	01/08	31/07	65	6-8 months
Humid forest	Rice	01/04	31/05	65	6-8 months
Southern guinean savannah	Rice	01/04	31/05	65	6-8 months
Southern guinean savannah	Sorghum	01/08	30/09	7-10	70-120 days
Northern guinean savannah	Sorghum	01/04	30/06	7-10	70-120 days
Sudanese savannah	Sorghum	01/04	30/06	7-10	70-120 days
Derived savannah	Cassava	01/03	31/08	6.913-1.3580	18-24 months
Humid forest	Cassava	01/03	31/08	6.913-1.3580	18-24 months
Northern guinean savannah	Cassava	01/03	31/08	6.913-1.3580	18-24 months
Sahelian savannah	Cassava	01/07	31/08	6.913-1.3580	18-24 months
Southern guinean savannah	Cassava	01/03	31/08	6.913-1.3580	18-24 months
Southern guinean savannah	Cotton	15/06	15/07	15	150-180 days
Northern guinean savannah	Cotton	01/07	15/07	15	150-185 days

Source: USDA and www.fao.org/agriculture/seed/cropcalendar/cropcalendar.do

3.2.3 Climate Variables

Temperature data

Three temperature variables, namely, average temperature, growing degree days (GDD) (10-32 degree), and Harmful Degree Day (HDD) (34 and above degree) termed are calculated from minimum and maximum daily temperature reported in NIMET. The data were gathered from all the weather stations scattered across the nation and cover January 1, 1991 to December 31, 2012. Missing values observed in the data were interpolated by taking a simple average of two dates that are adjacent to the missing period. In estimating the effect of extreme temperature on yield, it is essential that the data set contains sufficient instances of crop exposure to heat over 30 °C. Figure 1 shows the distribution of temperature by month for the nation. The frequency count was calculated using the daily maximum temperature value from 1991 to 2012. It shows the total occurrences of each 1 °C increment of recorded daily maximum temperature for all weather stations across the landscape for the entire period. The highest temperature in the weather dataset is 46 °C and occurred in March and April. The figure shows that temperature above 30 °C are common but above 40 °C less common. Daily maximums between 30 and 35 °C occurred more than a 1000 times for most of the months. Hence, this study assumes that sufficient occurrences of temperatures in the higher ranges exist in the dataset for a yield response to such temperatures to be analyzed econometrically. Various ways by which the temperature variables are defined are stated below.

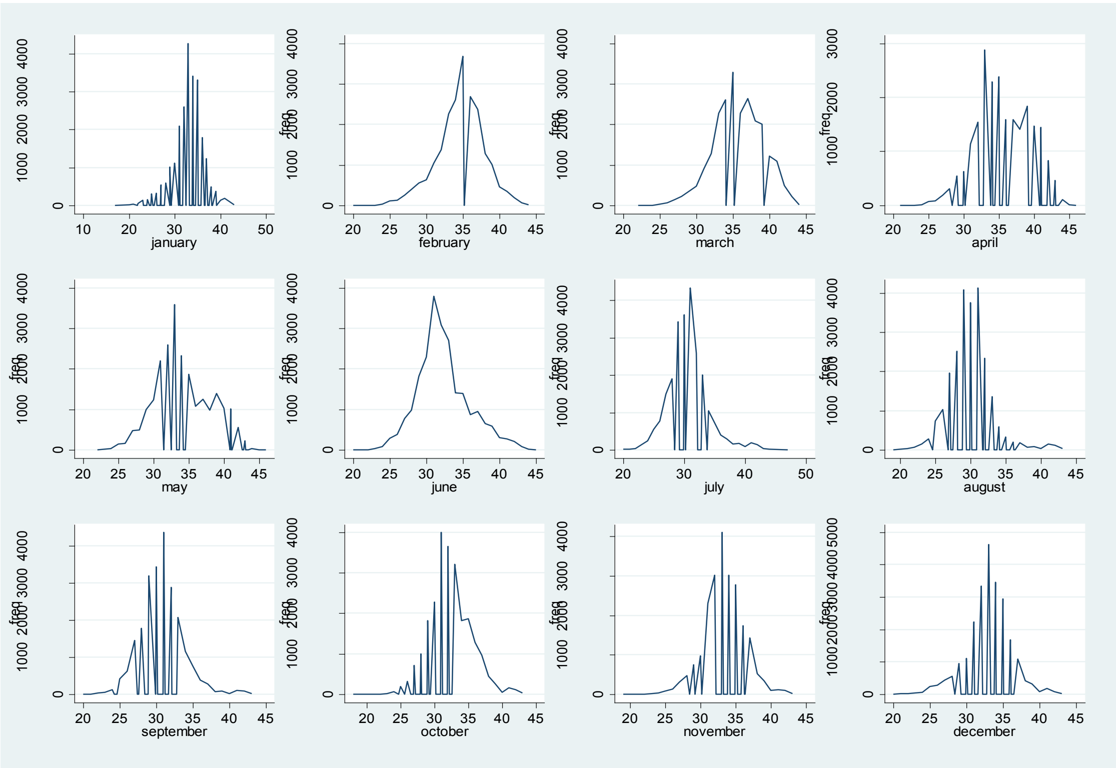

Figure 1: Frequency Distribution of Daily Temperatures (^{o}C) across all states by month

Average Temperature

TAVG = (Tmax + Tmin)/2 (7)

Where TAVG is the average temperature

Tmax is daily maximum temperature and

Tmin is daily minimum temperature

The growing season for each crop spread over several months, hence, the TAVG for each crop was averaged over the period across the producing states.

Growing Degree Days

A derivative of extreme temperature commonly used by agronomists to measure the number of heat units crops are exposed to during growing seasons is Growing Degree Days (GDD). The traditional way to calculate GDD is to measure the difference between mean daily temperature and a predetermined threshold (Robertson, 2012). If T_h is maximum temperature, T_i minimum temperature, T_b a given baseline temperature (usually between 8 and 10°C) and Tm a given upper bound (typically 30-32°C), then, over all days, growing degree days can be calculated as

$$GDD = \left\{ \frac{T_{h+}T_i}{2}, T_m \right\} - T_b \tag{8}$$

In this study, the baseline was assumed to be 10°C while the upper bound of 32°C was chosen. The use of mean daily temperature alone does not consider the fluctuation between daily maximum and minimum temperature. For example, 35 and 25 degrees have the same mean temperature (30 degrees) as 40 and 20 degrees, which is within the optimal temperature range (Lee, 2011). This study Follows Schlenker and Robert (2008), Robert et. al (2012) and Le (2011) in order to account for harmful growing degree days (HDD). In defining HDD, the lower bound is assumed to be 29°C and no upper bound. In multiple regression analysis, GDD is expected to influence yield positively while coefficient of HDD is expected to be negative.

Rainfall data

Rainfall data were also obtained from NIMET in the form of daily rainfall measured in mm. The data were summed over the entire growing season for each crop selected. Table 3 indicates the summary statistics. The lowest cumulative rainfall recorded for any growing season is 19.6 mm while the maximum is 4243.1 mm. The average varied from 469.7 mm to 1495.1 mm. Substantial differences exist in the observation for different crops perhaps due to spatial distribution. For instance, sorghum is predominantly grown in the Northern part while cassava thrives better in the south.

Table 3: Summary Statistics for Cummulative rainfall

Crop	Minimum	Year	Maximum	Year	Mean
Cassava	366.2	1999	4243.1	2008	1495.1
Maize	19.6	1992	2937.9	2009	1065.4
Cotton	426.6	1992	1789.4	1995	939.4
Rice	24.5	1992	2361	2004	469.7
Sorghum	366.2	1991	1935.4	2007	896.5

Vapor Pressure Deficit

Another variable of interest incorporated in the regression model is Vapor pressure deficit (VPD). VPD is calculated as the difference between how much water the air can hold when it is saturated and how much water it currently holds (Robert et al 2012). They approximated each day's VPD using the formular developed by Tetens (1930) as shown in equation 9.

$$VPD = 0.6107\left(\exp^{\frac{17.269Th}{237.3+Th}} - \exp^{\frac{17.269Ti}{237.3+Ti}}\right) \qquad (9)$$

Robert et al; 2012 show two ways by which VPD may either affect yield or be associated with weather patterns that affect yield. First, VPD drives water loss via plant transpiration, thereby increasing water requirements (Sinclair 2010). Second, VPD affects diurnal temperature variation, cloud cover and precipitation. VPD and water requirements are directly proportional while it has inverse relationship with cloud cover. Theoretically therefore, a positive relationship is expected between VPD and yield when soil moisture is adequate and a decreasing relationship when soils moisture is inadequate (Lobell 2007; Lobell, Bonfils, and Duffy 2007).

3.3 Sources of data

3.3.1 Yield

The yield data are obtained from the official records of each state Agricultural Development Programme. The data are available for all states in the country from 1991 to 2012. This is because about half of the states in the country were created in 1991.

3.3.2 Temperatures and Rainfall

The climate data were purchased from National Meteorological Agency in Lagos Nigeria for all the 32 weather stations across all the states in the country. The data consist of daily observations of maximum temperature (Tmax), minimum temperature (Tmin), and precipitation from January 1, 1981 to December 31, 2012. Each climate measure in the data set (AVG, GDD, HDD, VPD and RAIN) is calculated for each day. In order to obtain the state-level measures, averages of the variables were computed across states.

4.0 Regression Results and Discussion

The results reported in this section are based on Ordinary Least Square (OLS) analysis of the panel data. This is because OLS outperforms other estimators. Buddelmeyer et al., (2008) show that this is usually the case when the time dimension is short and number of observations is not large enough. The regression coefficients, t statistics, and adjusted-R^2 values of the OLS model for all the crops are shown in table 4. The model estimated using growing degree days (GDD and HDD) is selected for discussion. The selection is based on the significance of the variables, the models t and F statistics and acceptance of the Ramsey RESET test of no omitted variable bias.. The results for each crop are discussed below while the results of other models are presented in Appendix B.

4.1 Cassava

The result for cassava indicates a positive relationship between the yield of cassava and growing degree days.. A rise in growing degree days by 1^{o}C will cause an increase in cassava yield by about 0.0088 Kg/hectare. The marginal relationship of cassava yield with harmful degree days (HDD) is strongly negative. The result clearly implies that temperatures from 34^{o}C and above are harmful for the growth of cassava. A 1^{o}C increase in HDD will lead to about 0.18 kg/hectare decrease in cassava yield. In contrast to theoretical expectation, a negative relationship is exists between VPD and cassava yield. This implies that soils moisture for the growth of cassava in Nigeria is inadequate The fit of the model (adjusted R2 = 0.32) implies that about one third of the changes in the yield of cassava across Nigerian states is explained by changes in weather variables. Overall, the model is significant as shown by the significance of the F statistic at 1% probability level.

4.2 Cotton

The regression results for cotton shows negative relationship between the yield of cotton and precipitation. The marginal relationship with GDD is positive and statistically significant as expected apriori. A 1^{o}C rise in GDD will bring about 0.026 Kg/hectare increase in cotton yield. Like cassava, the relationship between cotton yield and HDD is strongly negative. A 1^{o}C increase in HDD will cause up to 0.18 Kg/hectare decline in cotton yield. This suggests that high temperatures can have serious damaging effects on cotton yield. In the augmented model, the coefficient of VPD is positive significant as expected theoretically. The fit of the model (adjusted R2 = 0.08) implies that about 8% of the changes in the yield of cotton across Nigerian states is explained by changes in the weather variables. Overall, the model is significant as shown by the significance of the F statistic at 1% probability level and the Ramsey reset test for omitted variable indicates that there is no problem of omitted variable bias.

4.3 Maize

The summary of the regression results for maize is presented in table 4 column 3. The result shows strong and positive relationship between the yield of maize and precipitation. The marginal relationship with GDD and HDD is weakly negative. Of the two however, the coefficient of HDD is statistically significant. This suggests high temperatures can be damaging to maize production, even when precipitation is not a constraint. A 1^{o}C increase in HDD will cause a decline of about 0.01 kg/hectare in maize yield. Like cassava, the coefficient of VPD in the augmented model is negative and significant at 10% significant level. The fit of the model (adjusted R2 =0.07) indicates slight difference relative to the simple correlation with HDD

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4.4 Sorghum

The regression coefficients, standard errors, and adjusted-R^2 values in respect of sorghum are reported in column 5 of Table 4. Like other crops, the result indicates positive and significant relationship between sorghum yield and precipitation. Like cassava, the marginal relationship with both GDD and HDD is negative and statistically significant. As with other crops, high temperatures from 34°C have damaging effects on sorghum yield. In the augmented model, the relationship of the yield with VPD is negative and significant. An increase in soil moisture is desirable in order to stimulate increase in the yield of sorghum. The fit of model (adjusted R2 =0.09) indicates considerable improvement relative to the simple correlation with HDD.

4.5 Rice

The regression results for rice are reported in the column 5 of table 4. The model shows strong and positive relationship with precipitation but no significant result is observed in the relationship of the yield with HDD. The marginal relationship with GDD is however found to be negative, indicating a damaging effect on the yield. The fit of the model (adjusted R2 = 0.08) also indicates considerable improvement relative to the simple correlation with HDD.

Table 4: Model using Growing Degree Days

Variable	Cassava	Cotton	Maize	Rice	Sorghum
Rainfall	.07152091***	-.24041106*	.05113968***	.1142399***	.07487107*
Rainfall^2	-.0000136***	0.00010489	-.00001141**	-.00002099*	-2.936E-05
GDD	.0087567*	.03062363***	-0.0003478	-.0283903**	-.0222793**
HDD	-.1757208***	-.17663581**	-0.014115*	0.03385219	-0.03625503*
Constant	108.49463***	17.080671	5.4742075	92.791658*	-477.3003***
r2_a	0.202	0.07804569	0.04081974	0.07227917	0.09533821
F	52.472	6.5658985	9.6496912	16.835303	7.0728381
Ramsey reset test	10.10	0.66	0.52	0.93	1.45
N	814	264	814	814	462

Source: Author's calculation

5.0 Conclusion and Implication of Results for Weather Index Insurance for Agriculture (WIIA)

This paper examined the effects of extreme weather on five major staple crops in Nigeria that occupied prominent position in the nation's agricultural transformation agenda. In all cases, there are expected harmful impacts from extreme weather. A high damage to all the crops (cassava, cotton, maize, sorghum and rice) is evident by the strong and negative coefficient of HDD. For cassava and sorghum an exposure to heat range that is expected to have positive effects on the yield is already showing negative influence. Given a clear evidence of increasing damage from extreme weather (HDD), the results are expected to have serious implication for crop productivity in the country. Possible adaptation measures to reduce the effects include development of irrigation and other infrastructure, flood control and improvement in crop varieties that are resistant to weather extreme. These measures are however costly and time consuming. An innovative way out of the problem is to incorporate weather index insurance in agriculture into the National Agricultural Insurance Scheme (NAIC). Although, crop insurance exists in Nigeria, it covers less than 1% of the total population of farmers. This is often applied when financial institutions impose them as a condition for formal credit. In addition to the need for expanded coverage of more farmers by the nation's crop insurance, the results underscore the imperative of reform of the national agricultural insurance scheme. It is high time the institution begins to think of a move towards a weather based insurance scheme.

The overriding aim of Weather Index Insurance for Agriculture (WIIA) is to alleviate the negative impacts of extreme weather on farming households and village economies by compensating part of the damage caused to farming products. Such insurance products are already available in Japan, the U.S. and EU member countries. In the scheme, insurance claims are paid according to the number of days when temperature either falls below or exceeds certain agreed levels, in order to compensate the income loss caused by the cold or the extreme heat. An advantage of WIIA is that, actual damage to crops in individual farmers need not be measured and verified. Instead, compensation is automatically paid out when a certain set of conditions are satisfied. Other advantages of index insurance include rapid payout and low transaction costs. However, in order to utilize WIIA the following points should be kept in mind:

(1) WIIA does not eliminate the risk of extreme weather conditions. Hence, considerable priority should still be placed on how to reduce greenhouse gas (GHG) emissions through mitigation measures.

(2) The Insurance does not eliminate the need for infrastructure development. It should be seen as a supplemental option. In this context, it should be considered as a short term approach to alleviate impact of extreme weather until infrastructure is fully developed and weather conditions return to their prior stable state.

References

Abbaspour, C. K., 1994: Bayesian risk methodology for crop insurance decisions. *Agric. For. Meteor.,* 71, 297–314.

Ajetomobi, J., Ajiboye, A. and Rashid., H. (2011). Impacts of climate change on rice agriculture in Nigeria. *Tropical and Sub-tropical Agro system* 14(2): 613-622

Ajetomobi J. O. and Ajiboye, A. (2010). Climate change impacts on cowpea productivity in Nigeria. African Journal of Food, Agriculture, Nutrition and Development 10(3): 2258-2271

Chalise, L and Ghimire, R 2013 Effect of Climate Change on Pea nut's Yield in the State of Georgia, USA. Paper presented at the Southern Agriculture Economics Association (SAEA) annual meeting, Orlando, Florida.

Dawson, P., & Lingard, J. (1982). Management bias and returns to scale in a Cobb-Douglas production function for agriculture. *European Review of Agricultural Economics* , 7-24.

Desjardins, R. L., Sivakumar, M. V., & de Kimpe, C. (2007). The contribution of agriculture to the state of climate: Workshop summary and recommendations. *Agricultural and Forest Meteorology, Vol. 142* , 314-324

Deuschênes, O., & Greenstone, M. (2007). The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather. *The American Economic Review, Vol. 97, No. 1* , 354-385.

Eickhout, B., Bouwman, A. F., & Zeijts. (2006). The role of nitrogen in world food production and environmental sustainability. *Agriculture, Ecosystems and Environment, Vol. 116* , 4-14.

Felkner, J., K.Tazhibayeva and R. Townsend. 2009. Impact of climate change on rice production in Thailand. American Economic Review 99(2): 205-210.

Féres, J. G., Reis, E. J., & Speranza, J. (2008). Assessing the Impact of Climate Change on the Brazilian Agricultural Sector. *Proceedings of the 36th Brazilian Economics Meeting, Brazilian Association of Graduate Programs in Economics*

Gay, C., F. Estrada, C. Conde, H. Eakin and L. Villers. 2006. Potential impacts of climate change on agriculture: A case study of coffee production in Veracruz, Mexico. Climate Change 79(3-4): 259-288.

Granger C. W. J and Newbold, P. (1973). Spurious regression in Econometrics. Journal of Econometrics 2:111-120

Hazell, P., C. Pomareda, and A. Valdes, 1986: *Crop Insurance for Agricultural Development: Issues and Experience.* John Hopkins University Press, 344 pp.

Jones P. G, Thornton P. K (2009) Croppers to livestock keepers: Livelihood transitions to 2050 in Africa due to climate change. Environ Sci Policy 12:427–437.
Just, R. E., & Pope, R. D. (1978). Stochastic Specification of Production Functions and Economic Implications. *Journal of Econometrics, Vol. 7* , 67-86.
Just, R. E., & Pope, R. D. (1979). Production Function Estimation and Related Risk Considerations. *American Journal of Agricultural Economics, Vol. 61, No. 2* , 276-284.
Le, P (2011) Climate Change Impact on Crop Yield: Re-examined Evidence from Decreasing Diurnal Temperature Range. Paper Presented at the 18th Annual Conference of the European Association of Environmental Economists, Rome, Italy.
Lobell, D. B. and J. Ivan Ortiz-Monasterio. 2007. Impacts of day versus night temperatures on spring wheat yields: a comparison of empirical and CERES model predictions in three locations. Agronomy Journal 99(2): 469-477.
Luo, Q (2011). Temperature thresholds and crop production: A review. Climate Change 109:583-598.
Mendelsohn, R. (2009). The Impact of Climate Change on Agriculture in Developing Countries. *Journal of Natural Resources Policy Research, Vol. 1, No. 1* , 5-19.
Mendelsohn, R. and M. Reinsborough. 2007. A Ricardian analysis of US and Canadian farmland. Climatic Change 81: 9-17.
Nhemachema C and Hanan, R. 2007. Micro analysis of farmers adaptation to climate change in south Africa IFPRI discussion paper 00714
Ray, P. K., 1967: *Agricultural Insurance, Principles, and Organization and Application to Developing Countries.* Pergamon Press, 489 pp.
Robertson S. M. (2012). A spatial model of agricultural land use with climate change for the Canadian priaries. A PhD thesis department of agricultural and resource economics university of Alberta.
Rosenweig, C and Parry, M. L 1994, potential impact of climate change change on wood food supply. Nature, January 1994
367 (6459) : 133-138
Rosenzweig, C. and M. Parry. 1997. Potential impact of climate change on world food supply. Chapter 6 in The Economics of Climate Change, Tom Tietenberg, ed. Cheltenham, UK: Elgar pp.118-136.
Schlenker, W and Roberts, M. (2006). Non linear effects of weather on crop yields: Implication for climate change. Working paper.

Tani, N., 1966: On the prevention measure of the damage from tyhoon in south Kyushu. *Bull. Kyushu Agric. Exp. Station,* 12, 343–387.
Wang, J., R. Mendelsohn, A. Dinar, J. Huang, S. Rozelle, and L. Zhang. 2009. The impact of climate change on China's agriculture. Agricultural Economics 40(3): 323-337.
Wooldridge, J. M. (2002). *Econometric Analysis of Cross Section and Panel Data.* Cambridge and London: The MIT Press.
Zhang, B., & Carter, C. A. (1997). Reforms, the Weather, and Productivity Growth in China's

Appendix A

Table A1: Average Yield of Selected Crops by State

Cassava	Cassava	Cotton	Maize	Rice	Sorghum
ABIA	19.18		1.65	1.89	
ADAMAWA	3.60	1.25	1.27	1.58	1.25
AKWA IBOM	9.46		1.28	3.30	
ANAMBRA	14.04		1.91	2.28	
BAUCHI	7.88	1.56	1.85	1.60	1.00
BAYELSA	11.05		1.39	2001.50	
BENUE	12.37		1.29	2.06	1.55
BORNO	3.60	4.65	1.20	1.18	1.34
CROSS RIVER	13.64		1.97	1.41	
DELTA	12.71		1.74	4.98	
EBONYI	12.27		1.38	2.47	
EDO	11.59		1.72	2.69	
EKITI	17.68		2.40	2.28	
ENUGU	10.69		1.71	3.13	
F.C.T.	6.08		2.63	1.07	0.66
GOMBE	2.53	1.46	1.70	2.22	1.12
IMO	15.21		2.23	0.62	
JIGAWA	2.60		0.81	1.16	0.59
KADUNA	11.83	3.18	2.68	2.68	1.90
KANO	2.60	1.38	1.72	1.61	1.50
KATSINA	11.00	1.17	0.95	1.39	0.92
KEBBI	18.15	0.75	4.65	1.71	1.03
KOGI	15.47		1.68	2.02	1.10
KWARA	13.13		1.28	2.45	1.34
LAGOS	12.59		2.34	1.73	
NASSARAWA	14.76		1.73	2.03	1.43
NIGER	10.32	0.79	1.46	1.67	0.93
OGUN	13.93		2.29	1.40	
ONDO	18.26		2.93	2.33	
OSUN	16.90		1.86	1.37	
OYO	9.98		2.35	1.37	1.31
PLATEAU	11.53	0.64	2.06	2.55	1.70
RIVERS	10.34		1.59	3.30	
SOKOTO	3.09		1.25	0.95	0.60
TARABA	9.27	1.08	3.46	2.07	1.47
YOBE	3.60		0.52	1.09	1.21
ZAMFARA	3.09	1.69	1.62	1.09	1.79
Total	10.70	1.63	1.85	56.01	1.23

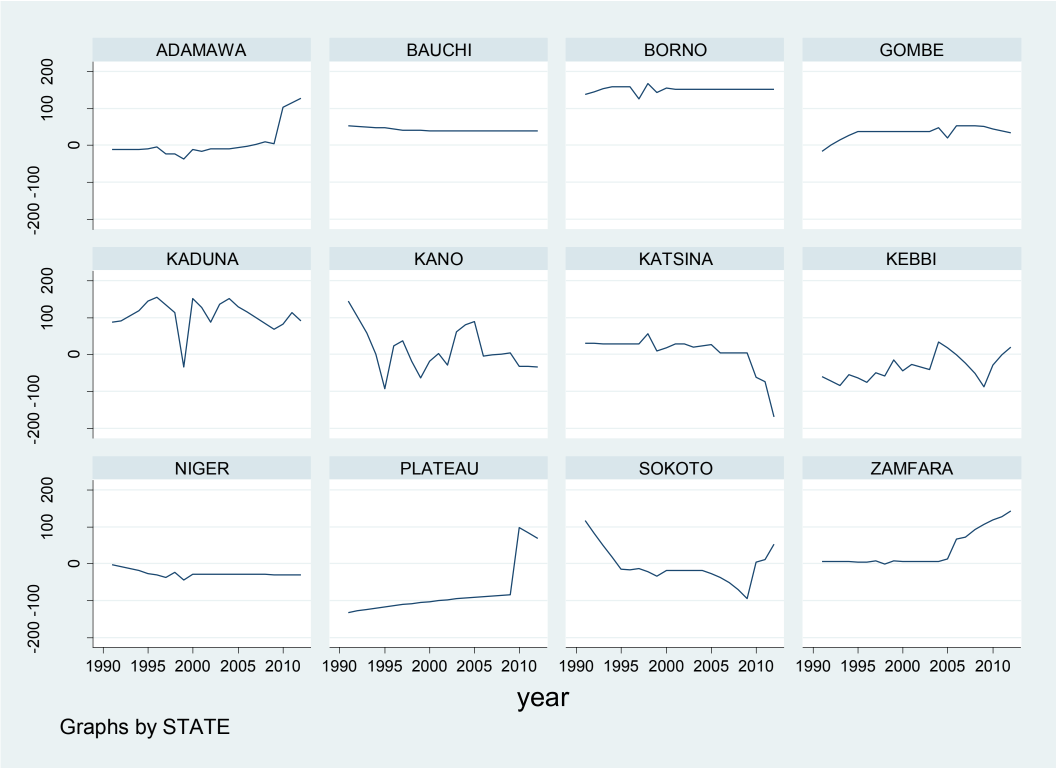

Figure 2: De-trended yield of cotton

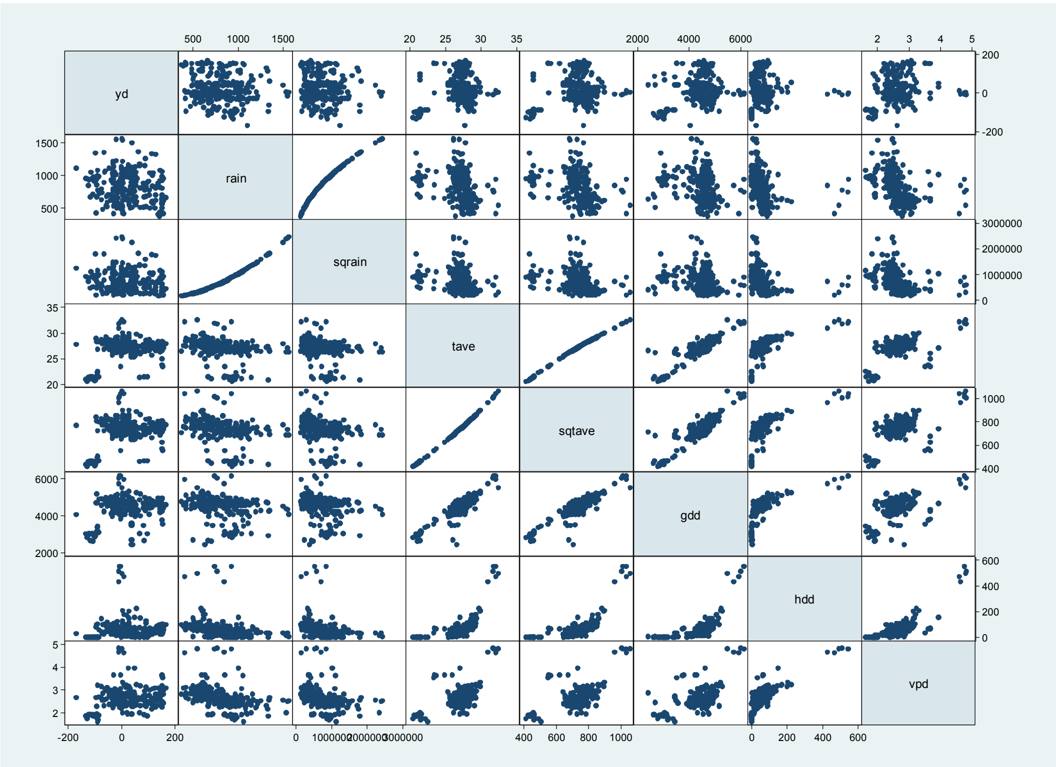

Figure 3: Scatter plot matrix for cotton variables

Table A2: Pair-wise Correlation of Cotton Variables

	Yd	Rain	sqrain	tave	Sqtave	gdd	hdd	vpd
yd	1							
rain	-0.185*	1						
sqrain	-0.161*	0.9839*	1					
tave	0.2554*	-0.323*	-0.289*	1				
sqtave	0.2316*	-0.334*	-0.301*	0.9975*	1			
gdd	0.1969*	-0.211*	-0.194*	0.8743*	0.8753*	1		
hdd	0.0379	-0.294*	-0.275*	0.6216*	0.6663*	0.6225*	1	
vpd	0.2519*	-0.405*	-0.377*	0.6403*	0.6600*	0.5574*	0.8204*	1

Figure 4: Cassava De-trended yield

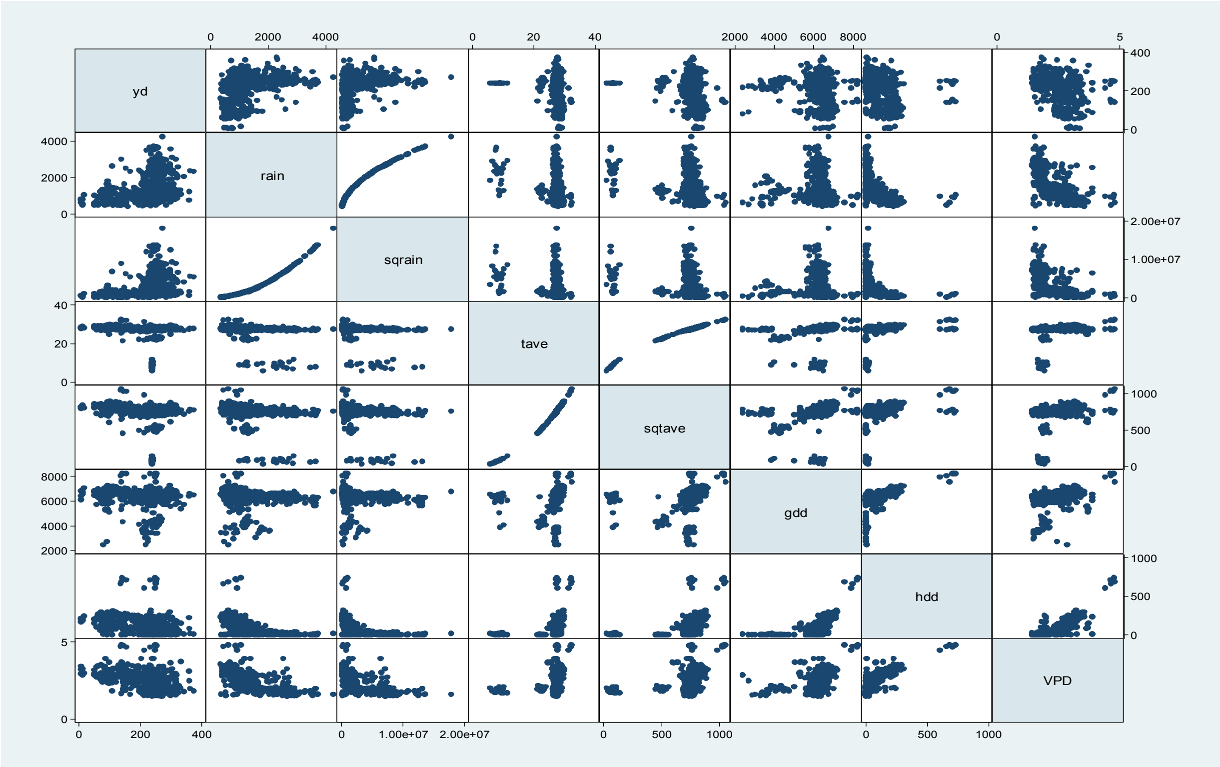

Figure 5: Scatter Plot Matrix of Cassava Variables

Table A3: Pair-wise correlation of cassava variables

	Yd	Rain	sqrain	Tave	Sqtave	gdd	Hdd	vpd
Yd	1							
Rain	0.3697*	1						
Sqrain	0.3167*	0.9746*	1					
Tave	-0.136*	-0.241*	-0.219*	1				
Sqtave	-0.169*	-0.261*	-0.232*	0.9879*	1			
Gdd	-0.0562	-0.0284	-0.0186	0.2569*	0.3317*	1		
Hdd	-0.378*	-0.524*	-0.447*	0.3004*	0.3747*	0.5105*	1	
Vpd	-0.462*	-0.624*	-0.555*	0.2962*	0.3517*	0.3925*	0.8531*	1

Figure 6: Scatter Matrix of Maize Variables

Figure 7: De-trended yield of maize

Table A4: Pair-wise correlation of maize variables

	YD	Rain	Sqrain	tave	Sqtave	gdd	hdd	Vpd
YD	1							
rain	0.0948*	1						
sqrain	0.0846*	0.9734*	1					
tave	-0.142*	-0.368*	-0.312*	1				
sqtave	-0.143*	-0.386*	-0.328*	0.998*	1			
gdd	-0.064	-0.118*	-0.105*	0.6262*	0.6288*	1		
hdd	-0.126*	-0.511*	-0.434*	0.7028*	0.7293*	0.6250*	1	
vpd	-0.108*	-0.574*	-0.509*	0.5895*	0.6064*	0.4386*	0.7068*	1

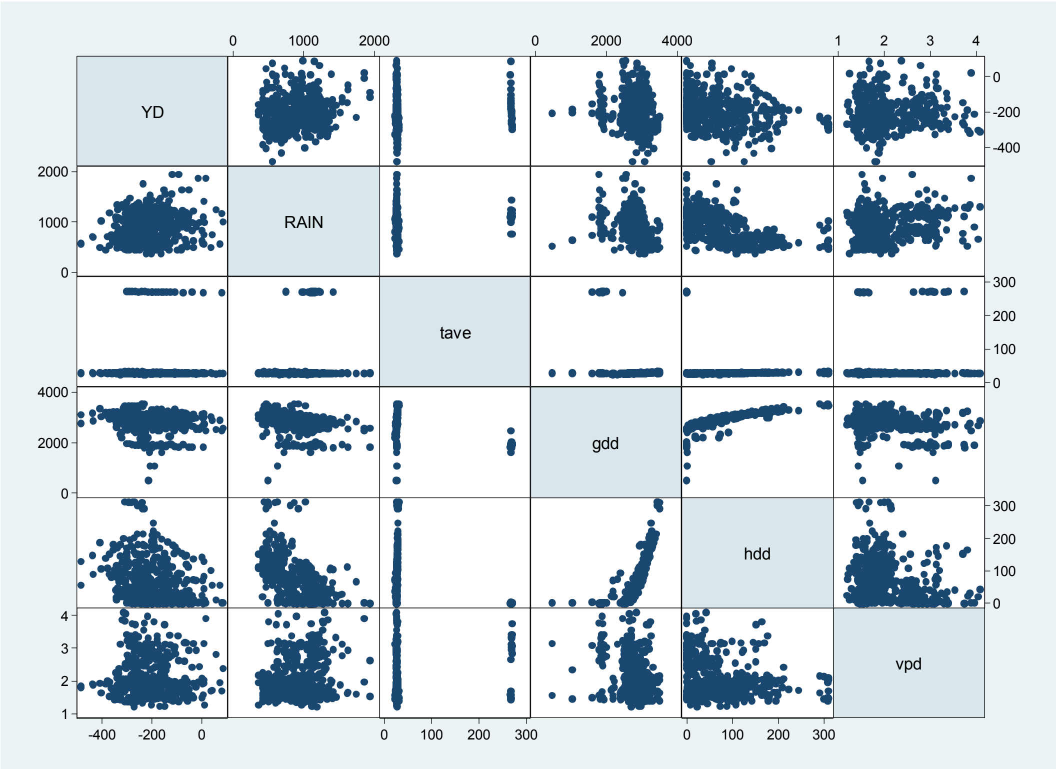

Figure 8: Scatter Plot Matrix of Sorghum Variables

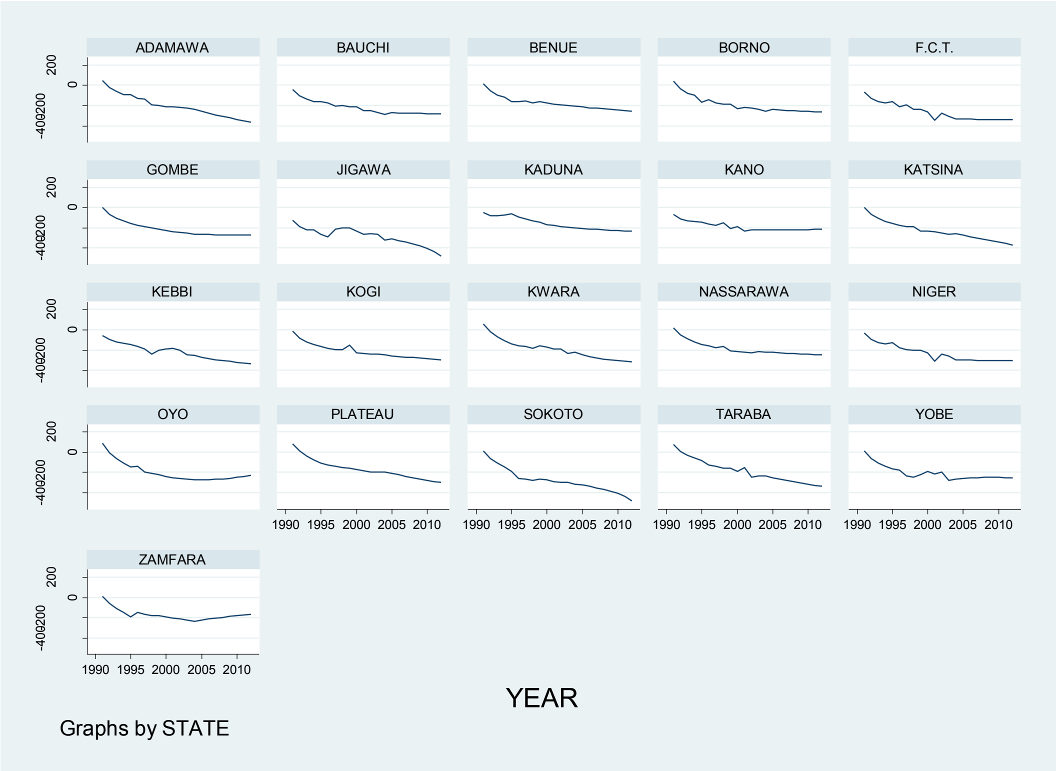

Figure 9: Detrended yield of sorghum

Table A5

	YD	Rain	Sqrain	Tave	Sqtave	gdd	hdd	Vpd
YD	1							
rain	0.1609*	1						
sqrain	0.1758*	0.9788*	1					
tave	0.0969*	0.1488*	0.1270*	1				
sqtave	0.0975*	0.1547*	0.1324*	0.9998*	1			
gdd	-0.130*	-0.359*	-0.334*	-0.447*	-0.455*	1		
hdd	-0.165*	-0.533*	-0.486*	-0.217*	-0.229*	0.7465*	1	
vpd	0.0175	0.2115*	0.2022*	0.1266*	0.1302*	-0.287*	-0.239*	1

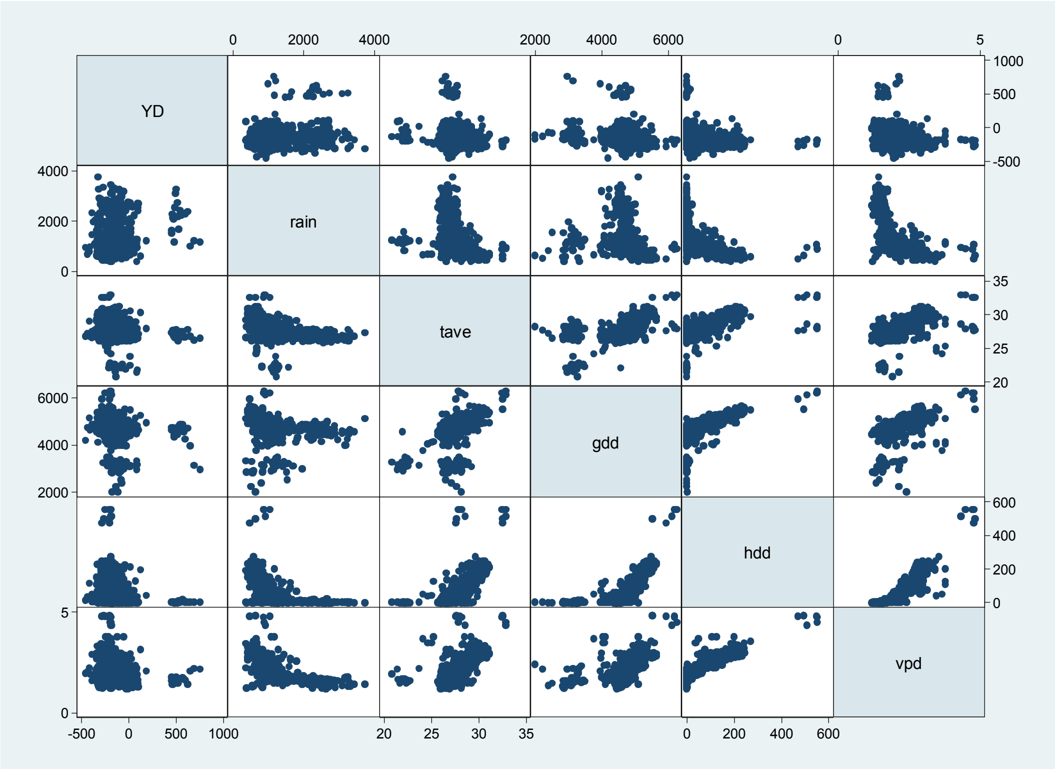

Figure 10: Scatter Plot Matrix for Rice Variables

Figure 11: De-trended yield of rice

Table A6: Pair-wise correlation of rice variables

	YD	Rain	sqrain	tave	Sqtave	gdd	Hdd	Vpd
YD	1							
rain	0.1977*	1						
sqrain	0.1758*	0.9763*	1					
tave	-0.156*	-0.359*	-0.294*	1				
sqtave	-0.161*	-0.377*	-0.309*	0.9980*	1			
gdd	-0.177*	-0.118*	-0.084*	0.582*	0.579*	1		
hdd	-0.198*	-0.471*	-0.393*	0.653*	0.678*	0.594*	1	
vpd	-0.205*	-0.579*	-0.507*	0.6225*	0.6437*	0.5126*	0.900*	1

APPENDIX B

Table B1: Model Using Mean Temperature and Rainfall

Variable	Cassava	Cotton	Maize	Rice	Sorghum
Rainfall	.10059857***	-.201874*	.0381353**	.09563935**	0.05916353
Rainfall^2	-.0000188***	0.00008268	-8.70e-06*	-1.742E-05	-0.0000221
temperature	18.543228***	180.60704***	2.7630096	35.261296	-4.532561*
Temperature^2	-.5058064***	-3.400722***	-0.1487141	-0.7689415	.01579367*
constant	-7.060	-2256.575***	52.503	-405.814	86.779205
F	48.960	16.884	13.978	14.720	8.9259704
Adjusted R-squared	0.19	0.19	0.06	0.06	0.06
Ramsey reset test	0.56	2.29	0.80	0.28	1.20
N	814	264	814	814	462

Table B2: Model using Growing Degree Days

variable	Cassava	Cotton	Maize	Rice	Sorghum
Rainfall	.07152091***	-.24041106*	.05113968***	.1142399***	.07487107*
Rainfall^2	-.0000136***	0.00010489	-.00001141**	-.00002099*	-2.936E-05
GDD	.0087567*	.03062363***	-0.0003478	-.0283903**	-.0222793**
HDD	-.1757208***	-.17663581**	-0.014115*	0.03385219	-0.03625503*
Constant	108.49463***	17.080671	5.4742075	92.791658*	-477.3003***
r2_a	0.202	0.07804569	0.04081974	0.07227917	0.09533821
F	52.472	6.5658985	9.6496912	16.835303	7.0728381
Ramsey reset test	10.10	0.66	0.52	0.93	1.45
N	814	264	814	814	462

Table B3: Model Using Growing Degree Days Augmented with VPD

Variable	Cassava	Cotton	Maize	Rice	sorghum
Rainfall	.0550927***	-0.1492368	.03854643**	.10569029**	.0775131*
$Rainfall^2$	-.00001197**	0.00007134	-9.388e-06*	-.00002034*	-2.963E-05
GDD	.00998254**	.02624564**	0.00195651	-.0272333**	- .0251301***
HDD	0.012	-.5675707***	0.04251813	0.16993354	0.0380459
VPD	-49.05929***	83.674811***	-17.8872***	-25.45865	-7.7076104*
Constant	221.88252***	-212.33032**	43.988931*	146.18406*	48.564735
r2_a	0.242	0.1798992	0.05956886	0.07341672	0.06406878
F	52.779	12.389483	11.299422	13.883417	7.3115128
Ramsey reset test	60.945	64.972519	50.559649	121.80383	43.079567
N	814	264	814	814	462