Sensitivity of crop yield to extreme weather in Nigeria[1]

BY

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Abstract

This study analyzed how extreme weather conditions affect the mean and variability of the yields of 11 staple crops in Nigeria. The research involved the use of a pooled panel data of 36 states and the federal capital territory over the period of 1991-2012. The framework for analysis consisted of the production risk model developed by Just and Pope for yield estimation. Unit root tests and Maximum Likelihood Estimation techniques were used to obtain reliable estimates of the model's parameters. The results showed that the mean and variance of the yield of all the staple crops were diversely influenced by extreme weather events.

Keywords: Extreme Weather, Yield Response, Climate, Unit Roots, Pope and Just Model, Nigeria
JEL Code: D24, C23

1.0 Introduction

Agriculture is inherently risky. Farmers usually lack knowledge of the precise output at the time of their production and input decisions. This is 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 have serious effects on agriculture. Weather extremes and climate anomalies can affect yields and disease patterns. For instance, when Droughts is followed by intense rains, it 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. This has 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 is devoted by Nigerian governments 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.

Even though risk analysis is a very important topic for agricultural production both from a policy and an academic perspective, most scholars so far have not paid appropriate attention to the risk aspect, in particular not to climate-related risks. Specifically, empirical studies such as Zhang and Carter (1997), and Ajetomobi and Ajiboye 2010 take climate variables as normal inputs in production, whereas Nhemachema and Hassan (2007) and Mendelsohn (2009) study the impacts of climate variables on farmers' net revenues. However, the issues of production risk stemming from climate factors and standard physical inputs as well as farmers' possibilities to adapt to this risk have not been systematically examined in the Nigerian context. This is necessary to guide the nation's agricultural insurance corporation on how best to protect farmers in the face of climate-related risks. Thus, this study is proposed to assess the effects of extreme weather on the mean and variability of the yields of major staple crops in Nigeria. In specific terms, the main objectives of this paper are to:

1) estimate the effect of extreme temperatures and rainfall during the growing season on yields for the following major Nigerian staple crops: cassava, cocoyam, cotton, cowpea, groundnut, maize, melon, millet, rice, sorghum, and yam.
2) estimate the effect of extreme temperatures and rainfall during the growing season on yield variability for the following major Nigerian staple crops: cassava, cocoyam, cotton, cowpea, groundnut, maize, melon, millet, rice, sorghum, and yam.

The study tests the following hypotheses stated in null form

1) H_{o1}: Exposure of crops to temperatures above a critical maximum point will have a positive effect on yield and exposure to temperatures below this point will have a negative effect on yield.
2) H_{o2}: Exposure of crops to rainfall above a critical maximum point will have a positive effect on yield and exposure to rainfall below this point will have a negative effect on yield.
3) H_{o3}: Exposure of crops to temperatures above a critical maximum point will have a positive effect on yield variability and exposure to temperatures below this point will have a negative effect on yield variability.
4) H_{o4}: Exposure of crops to rainfall above a critical maximum point will have a positive effect on yield variability and exposure to rainfall below this point will have a negative effect on yield variability.

2.0 Literature Review

Traditionally, time series data of crop yields have been used to assess the influence of year-to-year weather fluctuation on crop yields, either for specific climatic regions or by relying on a panel. Rosenzweig and Parry (1994) use calibrated crop-models to examine the effect of year-to-year weather fluctuation on crop yields to estimate the effect of changing climate conditions on yields and simulate farm adaptation. Deschenes and Greenstone (2004) use a panel data set to estimate the relation between profits and climatic variables. The authors regress profits in a county on climatic variables using county fixed effects.

Chalise and Ghimire 2013 utilize the 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 whole 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 very 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. the climate variables and the district dummies are vectors.

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

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 the 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 Model Specification

In order to account for the effects of the weather variables on the probability distribution of each crop yield, the stochastic production function introduced by Just-Pope (1979) was estimated from each crop panel data. The model has been widely employed by applied economist and it is still very much adopted in recent studies (Khumbhakar and Tveteras, 2003, Chen et. al; 2004, Kim and Pang, 2009). Following Just and Pope (1979), the production function is given by

$$Y = f(X,\beta) + h(X,\alpha)\varepsilon \quad E(\varepsilon) = 0, \mathrm{var}(\varepsilon) = 1 \tag{2}$$

Where *Y* is the crop yield (cowpea, corn, cotton, groundnut, sorghum, cassava, maize, melon, rice, cocoyam, and yam), *f(≅)* is an average production function, and X is a set of independent explanatory variables (climate, location, and time period). The functional form h(≅) for the error term ε, is an explicit form for heteroskedastic errors, which permits estimation of variance effects. Estimates of the parameters of f(≅) give the average effect of the independent variables on yield, while h(≅) gives the effect of each independent variable on the variance of yield as follows

$$E(Y) = f(X,\beta) \text{ and } \mathrm{var}(Y) = h^2(X,\alpha) \tag{3}$$

. The interpretation of the signs and magnitudes on the parameters of h(≅) are straightforward. If the marginal effect on yield variance of any independent variable is positive, then increases in that variable increase the standard deviation of yield, while a negative sign implies increases in that variable reduces the yield variance. Cobb Douglas and linear production form are chosen for the average yield function, f(X). The functional forms are consistent with the Just and Pope postulates which is an additive interaction between the average and variance functions.
the basic model in linear form is specified as:

$$Y_{it} = \exp(\alpha_0 + \sum_{k=1}^{k} \alpha_k X_{kit}) + \alpha_t Trend + \varepsilon_{it}\sqrt{\beta_0 + \sum_{m=1}^{m} \beta_m X_{mit}} \tag{4}$$

Where Y_{it} is the crop output in region i at time t; X_{kit} is the input quantity of factor k in region i at time t, and $\alpha_j, j = 0,1........k$,, are the parameters to be estimated. X_{mit} denotes a factor which can influence the risk level and β_m is the corresponding coefficient. ε is a stochastic disturbance term following the standard normal distribution. Thus, the expected output (often called the mean output) and the variance of output are determined by separate functions, which can algebraically be denoted as

$$E(Y_{it}) = \exp(\alpha_0 + \alpha_t Trend + \sum_{k=1}^{k} \alpha_k X_{kit}) \text{ and } V(Y_{it}) = \beta_0 + \beta_t Trend + \sum_{m=1}^{m} \beta_m X_{mit} \tag{5}$$

Given the assumption that production risk in this framework takes the form of heteroskedasticity in the production function, the second term on the right-hand side of equation (4) can be interpreted as a heteroskedastic error term for the purpose of estimation. The difference between the linear and the Cobb Douglas functional forms is that the variables in the latter are expressed in logarithmic form. The better functional form for each crop depends on the results of the diagnostic tests, namely, Wald chi square, log-likelihood, Akaike Information Criteria (AIC) and Bayesian Information Criteria.
The two commonly used approaches for estimating equation (5) are (i) Feasible Generalized Least Square (FGLS) suggested by Just and Pope (1979) and (ii) Maximum Likelihood Estimation (MLE) introduced by Saha, Havenner and Talpaz (1997). Under a small sample, the MLE has been proven to provide better efficient estimates when compared with FGLS (Saha et.al; 1997). The log-likelihood function is

$$\ln L = -\frac{1}{2}\left[n\ln(2\pi) + \sum_{i=1}^{n} \ln h^2(X,\alpha) + \sum_{i=1}^{n} \frac{Y_i - f(X,\beta))^2}{h^2(X,\alpha)} \right] \quad (6)$$

3.2 Time Series Estimation

An assumption of the production model is that the variables used are stationary. Deterministic and stochastic trends in variables can introduce spurious correlations between the variables, because the errors in the data-generating-processes for different series might not be independent (Granger and Newbold, 1974). The solution to these problems is to first test for stationarity of the variables. Non-stationary variables can be differenced once and retested. If the differenced versions are stationary, the variables are said to be integrated of order one or I(1). If they are Stationary at levels, then the time series are integrated of order zero or I(0). Regressions on stationary variables may satisfy ideal conditions, and inferences on a deterministic time trend can be made safely. There are several versions of these so-called panel unit root tests due to Im, Pesaran, and Shin (1997), Levin and Lin (1992, 1993) and Hadri Z. Im et.al; 1997 was used in this study. The test is applied to each variable, taking the whole panel at once. In 1997, Im et al. show that the test has a better finite sample performance than other approaches. The test is valid when region regressions are serially uncorrelated and normally and independently distributed across regions. As long as the number of regions is large relative to the number of time period, the test statistic is normally distributed. For cassava, the data is made up of 726 observations with 22 years of data across 33 states in the country. There are 748 observations for maize with 22 years of data across 34 states of the federation.
Given that the yield or weather variable is a stochastic first order auto regressive process for region i in time t,

$\Delta Y_{it} = \alpha_i + \beta_i Y_{i,t-1} + \varepsilon_{it}$ i = 1, ……., N; t = 1, …………….., T, (7)

Where ΔY_{it} and ε_{it} are independently and identically distributed across region i and time t. The null hypothesis of a unit root in (7) is tested as
Ho: $\beta_i = 0$ for all *i*.

The models (unit roots and MLE) were estimated for each of the major staple crops in Nigeria. As the production function is specified in a log-linear way, the coefficient estimates showed the elasticities of each crop output with respect to the respective input factors.

3.3 Variable Measurement

Extreme Temperature

In this paper, heat index is used as the indicator of extreme temperature. The heat index is defined as the number of days per month with maximum temperature exceeding a certain threshold T^*, e.g. $T_{\max} > T^*$ while heat-wave is defined as a continuous period (2 days or more) with daily maximum temperature exceeding 30^{o}C. For this study, all the approaches will be tried to find out which one explain changes in crop yield in Nigeria.

Extreme Precipitation

Precipitation (P) was measured as the accumulated total over the crop growing season, measured in centimeters. To compute extreme events for precipitation the number of days which have 95-percentiles of the daily precipitation was used.

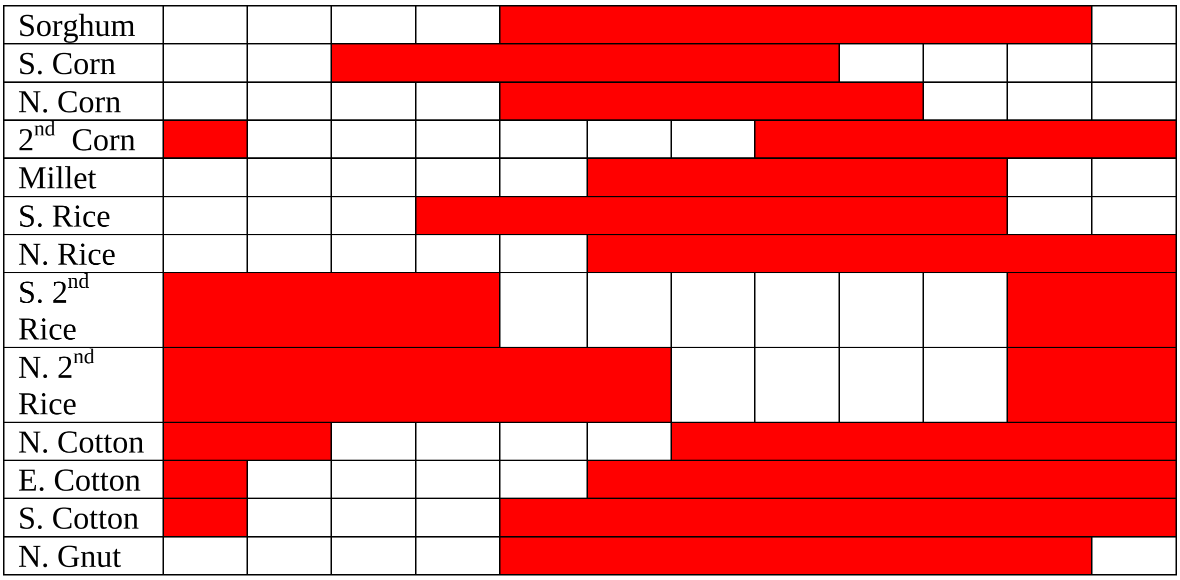
3.4 Sources of data

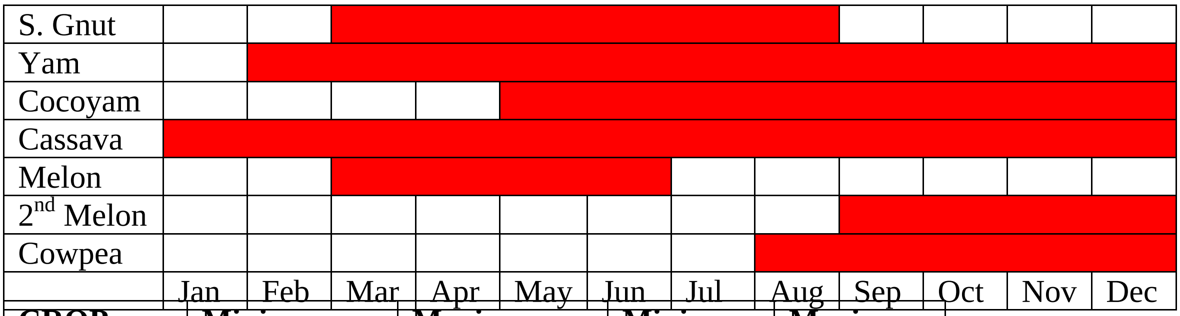
The yield data are obtained from the official records of each state Agricultural Development Programme. The data are available for all states in the country from 1991 to 2012. This is because about half of the states in the country were created in 1991. The climate data were purchased from National Meteorological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

4.0 Results and Discussion

4.1 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. The growing seasons for the selected crops are shown in Table 1. The growing seasons vary, depending on whether the crop is grown in the northern or southern part of Nigeria. In addition, maize, rice, groundnut and melon have two growing seasons in the country.





CROP	Minimum Temperature	Maximum Temperature	Minimum Rainfall	Maximum Rainfall
Rice	10	35	600	1000
Maize	15	35	500	800
Sorghum	10	35	450	650
Millet	10	35	450	650
Yam	20	40	1200	2000
Groundnut	10	35	600	1250
Cotton	10	40	500	1200
Melon	15	30	400	700
Cassava	15	40	800	1200
Cocoyam	15	40	1250	2200
Cowpea	10	32	400	750

Table 1: Growing seasons of staple crops in Nigeria Note: “S” stands for southern part, “N” stands for northern part, “2nd “ means second season and “Gnut” means groundnut

The temperature threshold used to construct the hot day heat index for various crops are shown in Table 2. For the cereals, the threshold is 35^{o}C while for tubers, it is 40^{o}C. The crop with the lowest threshold is melon (30^{o}C).

Table 2: Temperature Threshold for Staple Crops in Nigeria

Sources: Luo 2011

Production functions were estimated for the first growing seasons in respect of maize, melon rice and groundnut. This is because of data inconsistencies and scarcity.

Fig 1 above shows the descriptive statistics of the average yield of staple crops in Nigeria between the period of 1991 to 2012. The graph shows that over the entire analysis period, yam has the highest yield and exhibits an upward trend. It is followed closely by cocoyam and cassava. The result shows that root and tuber crops have an edge over all other staple crops in Nigeria. This may be due to higher demand and favourable climatic conditions. The yield of other crops is less than 3 tons per hectares over the analysis period.

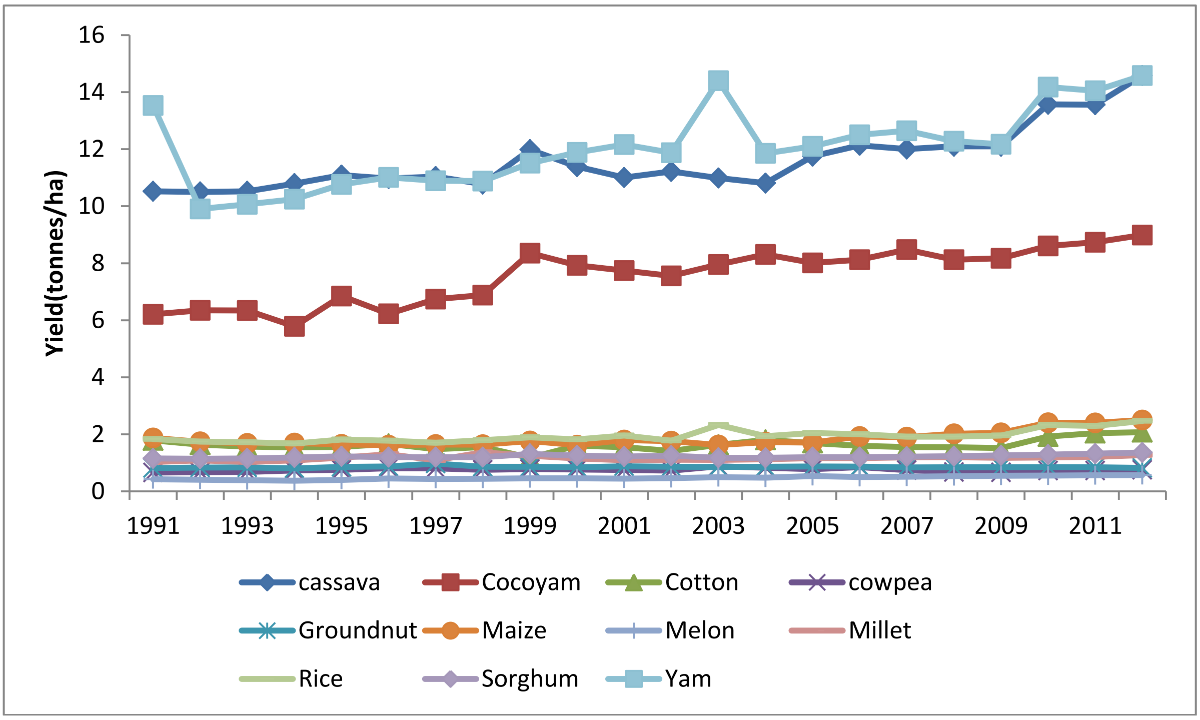


Figure 1: Average Yield of Staple Crops in Nigeria (1991 - 2012)

The descriptive statistics for the crops over the analysis period are shown in appendix A, The total number of observation used for data analysis varies from 264 for cotton to 814 for rice over the analysis period (1991-2012). The difference is a reflection of the number of states producing the crops. For instance, cassava is grown in 33 states while rice is grown in 34 states. This translates to 726 and 748 observations for cassava and rice respectively over the 22 years considered for the analysis. The mean yield over the period is generally higher for tuber crops (cassava, cocoyam and yam) than other crops. The mean yield for cassava, for instance, is 11.61 tonnes/ha while it is 1.85 for maize.

The number of days with extreme temperature and rainfall vary from crop to crop. The average number of days with exposure to heat above the temperature threshold is 6.25 for cassava, 44.60 for cowpea, and 72.89 for rice. The number of days with extreme rainfall for the crops is 17.79, 5.45 and 14.39 for cassava, cowpea and rice respectively.

4.2 Time Series Properties of the Regression Variables

In 1997, Im et al. introduced a series of unit root test statistics in heterogeneous panel regression to establish the stationarity of variables. The LM bar test is based on the mean of the individual unit root statistics. The test is valid when the errors in the region regression are serially correlated, and normally and independently distributed across region. Under these circumstances LM-bar is distributed as standard normal as long as the number of region is large relative to the number of time periods. Under the assumption of serially uncorrelated errors, the LM-bar statistics used to test this null hypothesis is define by $_{L_{LM}} =$

$$\sqrt{N}\left\{\bar{LM}_{NT} - E(\eta_T)\right\} / \sqrt{Var(\eta_t)}$$

LM- bar is the simple average of region Lagrange Multipliers. This avoids possible spurious correlation between variables and allows the establishment of valid relationship.

The table above shows the results from applying the panel unit root test procedure to all individual variables of yield, heat index rainfall and 95 percentiles of rainfall.

Table 3 shows the results from applying the panel unit root test procedure to all individual variables of yield, hot day heat index, rainfall and 95 percentiles of rainfall. The Table shows that all the variables are stationary at levels for each crop. In other words, they are integrated of order zero I(0), thereby rejecting the null hypothesis of a unit root test. The tests reject the hypothesis of a unit root in all the variations of IPs tested. The interest of the study is that stationarity of all the variables are used in the panel production function model to avoid possible spurious correlation between variables and allows valid result

Table 3: IPS Panel Unit Root Test

No- Serial Correlation	Yield	Heat	Rain	Rain95
Cassava	-2.607*	-3.765	-3.390*	-3.983*
Cocoyam	-2.359*	-3.540*	-3.235*	-3.787*
Cotton	-2.527*	-3.873*	-4.211*	-4.432*
Cowpea	-2.325*	-3.764*	-4.353*	-4.826
Groundnut	-3.902*	-3.534*	-3.688*	-4.349*
Maize	-2.077*	-4.752*	-3.535*	-3.812*
Millet	-2.887*	-3.539*	-3.895*	-4.429*
Rice	-2.659*	-3.940*	-3.772*	-4.274*
Sorghum	-2.403*	-3.338*	-3.776*	-4.238*
Yam	-3.691*	-3.910*	-3.596*	3.979*
Melon	-2.882*	-3.759*	-3.172*	-3.744*
Serial correlation	Yield	Heat	Rain	Rain95
Cassava	-1.687*	-6.757*	-8.052*	-11.662*
Cocoyam	0.409*	-7.697*	-6.350*	-8.098*
Cotton	-1.011*	-6.176*	-8.053*	-9.101*
Cowpea	-0.812*	-3.765*	-13.128*	-16.642*
Groundnut	-10.412*	-7.136*	-8.211*	-10.911*
Maize	1.569*	-9.073*	-11.724*	-11.454*
Melon	-3.101*	-6.378*	-5.322*	-12.184*
Millet	-3.428*	-6.801*	-8.699*	-11.449*
Rice	-3.109*	-10.30*	-9.670*	-10.898*
Sorghum	-0.732*	-6.513*	-8.323*	-11.680*
Yam	-9.018*	-10.681*	-8.279*	-10.934*
Correlation across groups	Yield	Heat	Rain	Rain95
Cassava	-2.284*	-4.051*	-3.362*	-3.549*

Cocoyam	-2.753*	-3.744*	-3.150*	-2.575*
Cotton	-2.462*	-4.662*	-4.215*	-2.419*
Cowpea	-2.518*	-4.974*	-4.323*	-3.868*
Groundnut	-3.969*	-3.193*	-3.557*	-4.431*
Maize	-2.159*	-4.527*	-3.815*	-4.911*
Melon	-3.073*	-4.239*	-3.214*	-3.133*
Millet	-2.976*	-4.515*	-3.908*	-3.104*
Rice	-3.609*	-4.209*	-3.461*	-3.837*
Sorghum	-2.577*	-4.312*	-3.673*	-3.450*
Yam	-4.933*	-4.303*	-3.630*	3.952*

Note: This table report three versions of Im et al.'s LM-bar test statistics. "Serial correlation" statistics are robust to error term serial correlation, while "correlation across groups" statistics are robust to serial correlation in the cross-section dimension

Key: * Null hypothesis of non-stationary is rejected with 99% confidence.

4.3 Just and Pope Modelling of the Crop Yield and Variability Functions

Two specifications of the production function are tested, namely, linear and Cobb- Douglas production functions. The value of Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC), Wald and Log likelihood are better in the Cobb Douglas (CD) result for all the crops, hence the CD results are discussed. The Cobb Douglas and Linear models are estimated using Maximum Likelihood Estimation (MLE) approach. The optimization procedure in STATA 11.2 program is employed to obtain the estimates. The estimated results show the effects of extreme weather variables on the average and the variability of crop yield. Regional dummies are dropped in the equations because most of them are insignificant. This might be because yield variability among regions is not quite different. The time trend variable is included to describe the technological process. The estimation results for the function are shown in appendix B, Table 1 to 11. The coefficients of the variables from the CD are interpreted as the direct elasticities.

Extreme temperature is negatively related to the average yield of cassava, cocoyam, cotton, millet rice, sorghum, yam and maize. A 1% rise in extreme temperature decreases the average cassava yield by 0.05%. For cocoyam, the extreme temperature elasticity is 0.02. This same value also applies for rice and yam which yield decreases by about 0.02% with 1% increase in extreme temperature. An increase in extreme temperature by 1% decreases the yield of millet by 0.007% while the extreme temperature elasticity of sorghum is found to be 0.03. For maize, a 0.01% decline in yield results from a 1% increase in extreme temperature. On the contrary, extreme temperature still has a positive influenced on the yield of groundnut, cowpea and melon. A 1% increase in in temperature increases groundnut, cowpea and melon yields by 0.0006, 0.031 and 0.31 % respectively. The crops are predominantly grown in Northern part of Nigeria.

Rainfall is also observed to have negative effects on cassava, rice and sorghum. It is noted that rainfall elasticity for these crops are 2.17, 5.11 and 2.52 respectively which implies an increase in rainfall by 1% will decrease the yield of the selected crops by 2.17, 5.11 and 2.52% respectively. For other crops, a positive correlation exists between extreme rainfall and their yields. In respect of the effects of total amount of rainfall over each crop growing season, the effect is negative for cotton and millet, insignificant for sorghum, yam, maize and melon and positive for cassava, cocoyam, groundnut and rice.

It is noteworthy that both temperature and precipitation enlarge the yield variability. The coefficient for temperature is statistically significant in both equations. A 1% rise in extreme temperature increase yield variability of cassava, cocoyam, groundnut, rice and maize by 4.8, 8.37, 11.42, 2.58 and 4.7% respectively. It has a negative effect on millet yield variability which decreases by 6.06% with a 1% rise in temperature. A 1% increase in extreme rainfall causes cassava, cocoyam, groundnut, and maize yield variability to increase by 5.25, 1.84, 3.18 and 6.33%. Altogether, it is expected that this crops yield variability may increase by about 2 - 6.5% when both temperature and rainfall increases by 1%. The increase crop yield variability can result in wide fluctuations in crop production and could make price unstable.

5.0 Concluding Remark

The tests in this paper used extreme weather indices to measure the impact of weather on crops' yield and their variability. The approach is an improvement over the direct use of weather variables in crop yield response regressions. The empirical results show that the two extreme climate variables have significant impact on the yield and the variability. This is expected to have some implication on planned climate adaptation initiatives.

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: Ajiboye, A and Hassan, R (2011). Impact of climate change on rice agriculture in Nigeria. Tropical and subtropical agrosystems. 14: 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.
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: Descriptive Statistics

Cassava

Variable	Obs	Mean	Std. Dev.	Min	Max
Yield	726	11.60969	5.537916	1.085	43.503
Heat	726	6.249311	14.1735	0	71
Rain	726	1495.103	739.4782	0	4243.1
rain95	726	17.78512	6.530615	0	56

Cocoyam

Variable	Obs	Mean	Std. Dev.	Min	Max
Yield	462	7.567429	8.164548	0.008	50.849
Heat	462	16.83117	41.12087	0	245
Rain	462	1508.325	649.9735	441.7	3522.9

rain95	462	8.937229	5.956673	0	28

Cotton

Variable	Obs	Mean	Std. Dev.	Min	Max
Yield	264	1.633527	1.27486	0.189	5.454
Heat	264	19.47727	34.33407	0	235
Rain	264	939.4057	290.5291	0	1789.4
rain95	264	15.44697	5.483212	4	53

Cowpea

Variable	Obs	Mean	Std. Dev.	Min	Max
Yield	704	0.752692	0.439484	0.057	4.741
Heat	704	44.60085	64.70332	0	1521
Rain	704	603.3238	327.3771	0	1931.7
rain95	704	5.454545	4.660378	0	62

Groundnut

Variable	Obs	Mean	Std. Dev.	Min	Max
Yield	660	0.856358	0.273253	0.069	3.172
Heat	660	34.46061	39.72336	0	214
Rain	660	1052.662	426.2183	0	2937.9
rain95	660	10.22424	4.462763	1	47

Maize

Variable	Obs	Mean	Std. Dev.	Min	Max
Yield	814	1.852947	1.101431	0.141	7.955
Heat	814	43.30958	245.5027	0	6936
Rain	814	1065.4	468.7166	0	2937.9
rain95	814	10.78624	6.109981	0	47

Melon

Variable	Obs	Mean	Std. Dev.	Min	Max

Yield	440	0.47598	0.23895	0.087	1.299
Heat	440	84.21818	44.80759	0	885
Rain	440	553.153	340.0819	0	1787.6
rain95	440	6.077273	3.109751	0	16

Millet

Variable	Obs	Mean	Std. Dev.	Min	Max
Yield	418	1.163593	0.471523	0.071	3.857
Heat	418	26.77033	33.06124	0	155
Rain	418	780.8227	245.6211	0	1562.5
rain95	418	7.710526	3.603879	0	36

Sorghum

Variable	Obs	Mean	Std. Dev.	Min	Max
Yield	418	1.163593	0.471523	0.071	3.857
Heat	418	26.77033	33.06124	0	155
Rain	418	780.8227	245.6211	0	1562.5
rain95	418	7.710526	3.603879	0	36

Yam

Variable	Obs	Mean	Std. Dev.	Min	Max
Yield	594	12.06839	7.080928	0.98	120.349
Heat	594	7.882155	34.24645	0	268
Rain	594	1677.128	756.5424	0	3854.5
rain95	596	15.62416	6.864084	0	37

Rice

Variable	Obs	Mean	Std. Dev.	Min	Max
Yield	748	1.942406	1.257582	0.18	17.083
Heat	748	72.8877	54.56419	0	196
Rain	748	469.7096	351.9039	0	2361

rain95	748	14.39037	7.116548	0	47

Appendix B: Results of the Production Function Estimate Using MLE Approach

Table: 1 Cassava estimation result

	Cobb Douglas function			**Linear function**		
Variable	**Coefficient**	**Std. Err.**	**Z**	**Coefficient**	**Std. Err.**	**Z**
Mean						
Heat index	-0.046**	0.008	-5.75	-0.079**	0.020	-3.92
Rain index	-0.092**	0.042	-2.17	0.001**	0.001	3.9
Rainfall	0.191**	0.042	4.52	-0.059**	0.031	-1.92
Trend	0.011**	0.002	4.9	0.140**	0.028	4.85
_cons	0.953**	0.273	3.49	10.011**	0.664	15.08
Std dev.						
Heat index	0.027**	0.005	4.8	0.036**	0.016	2.24
Rain index	0.143**	0.027	5.24	-0.001**	0.0001	-4.49
Rainfall	-0.276**	0.028	-9.65	0.048*	0.028	1.69
Trend	0.001	0.001	0.82	0.046**	0.018	2.52
_cons	2.148**	0.205	10.43	4.997**	0.613	8.14
Log Likelihood	-492.776**			-2205.38**		
Wald Chi2	123.52**			71.96**		
AIC	1005.552			4430.752		
BIC	1051.386			4476.628		
No of Obs	726			726		

Table 2: Cocoyam estimation result

	Cobb Douglas function			Linear function		
	Coef.	Std. Err.	Z	Coef.	Std. Err.	Z
Mean						
Heat index	-0.020*	0.011	-1.75	0.051**	0.020	2.53
Rain index	-0.106	0.106	-1	0.001*	0.001	1.56
Rainfall	0.362*	0.182	1.99	-0.066	0.062	-1.07
Trend	0.001	0.003	0.31	0.027	0.021	1.31
_cons	-0.765	1.139	-0.67	5.202**	0.569	9.14
Std dev.						
Heat index	0.083**	0.010	8.37	0.154**	0.014	11
Rain index	0.160*	0.087	1.84	-0.0008*	0.001	-1.73
Rainfall	-0.550**	0.157	-3.49	0.049	0.051	0.96
Trend	0.001	0.002	0.59	0.049**	0.012	3.95
_cons	4.499**	0.979	4.6	2.711**	0.389	6.96
Log Likelihood	-463.37**			1260.8**		
Wald Chi2	18.42**			9.64**		
AIC	946.747			2541.605		
BIC	987.972			2582.961		
No of Obs	462			462		

* means significant at 10% level; ** means significant at 5% level

Table 3: Cotton estimation result

	Cob Douglas			Linear		
	Coef.	Std. Err.	Z	Coef.	Std. Err.	Z
Mean						
Heat index	-0.010	0.043	-0.24	Heat	0.004	0.004
Rain index	0.155	0.169	0.92	Rain	-0.001	0.0003
Rainfall	-0.571**	0.2253	-2.54	rain95	0.035	0.020
Trend	0.002	0.008	0.25	trend	0.015	0.011
_cons	3.706**	1.3822	2.68	_cons	1.779	0.384
Std Dev.						
Heat index	0.047*	0.031	1.49	Heat	0.010	0.004477
Rain index	-0.023	0.141	-0.16	Rain	-0.0004	0.000255
Rainfall	-0.111	0.162	-0.69	rain95	0.039	0.017912
Trend	0.007	0.005	1.44	trend	-0.007	0.008006
_cons	1.265	1.037	1.22	_cons	0.897	0.350385
Log Likelihood	-184.626			-422.089		
Wald Chi2	10.17			15.77		
AIC	465.654			864.1785		
BIC	389.252			899.938		
No of Obs	264			264		

Table 4: Groundnut estimation result

	Cob douglas			Linear		
	Coef.	Std. Err.	Z	Coef.	Std. Err.	Z
Mean						
Heat index	0.001*	0.000334	1.84	-0.017*	0.0094*	-1.82
Rain index	-0.009	0.010	-0.48	0.034	0.0256*	1.36
Rainfall	-0.0004	0.002	-0.2	-0.085*	0.044*	-1.94
Trend	0.0006	0.001	0.52	0.004**	0.0019**	2.06
_cons	0.842**	0.033	25.51	0.311	0.297	1.05
Std Dev.						
Heat index	0.002**	0.000223	11.42	0.050**	0.005**	9.01
Rain index	4.25E-05**	1.34E-05	3.18	0.012	0.019	0.64
Rainfall	0.0008	0.0019	0.51	0.040*	0.025*	1.61
Trend	-0.004**	0.0008	-5.5	-0.004**	0.001**	-3.18
_cons	0.152**	0.020293	7.51	-0.092	0.154	-0.6
Log Likelihood	53.993**			53.993**		
Wald Chi2	5*			8.71*		
AIC	87.986**			285.439**		
BIC	43.064**			328.610**		
No of Obs	660			660		

Table 5: Millet estimation result

	Cobb Douglas			Linear		
	Coef.	Std. Err.	Z	Coef.	Std. Err.	Z
Mean						
Heat index	-0.007	0.0073	-1	-0.001*	0.0006	-1.93
Rain index	-0.045	0.043	-1.06	0.0002**	0.0001	2.16
Rainfall	0.149**	0.072**	2.07	-0.004	0.003	-1.34
Trend	0.004*	0.003*	1.57	0.007*	0.004	1.92
_cons	-0.872**	0.456*	-1.91	0.982**	0.088**	11.12
Std Dev.						
Heat index	-0.032**	0.005	-6.06	-0.001**	0.0006**	-2.37
Rain index	0.045	0.040	1.25	9.47E-05	7.07E-05	1.34
Rainfall	-0.106**	0.046	-2.28	-0.009**	0.003*	-3.49
Trend	0.008**	0.0018	4.1	0.009**	0.002**	3.98
_cons	0.959**	0.284	3.37	0.390**	0.074**	5.24
Log Likelihood	-203.81**			260.61**		
Wald Chi2	12.04**			19.47**		
AIC	427.63**			541.21**		
BIC	467.89**			581.57**		
No of Obs	414			414		

Table 6: Rice estimation result

	Cob douglas			Linear		
	Coef.	Std. Err.	Z	Coef.	Std. Err.	Z
Mean						
Heat index	-0.024**	0.008**	-2.96	-0.004**	0.000801	-4.92
Rain index	-0.156**	0.030**	-5.11	0.001**	0.000179	4.79
Rainfall	0.170**	0.024**	7.01	-0.015**	0.004838	-3.09
Trend	0.009**	0.003**	3.35	0.0153**	0.005072	3.03
_cons	-0.113	0.162	-0.7	1.890*8	0.146567	12.9
Std, Dev.						
Heat index	0.017**	0.006**	2.58	-0.004**	0.00053	-8.43
Rain index	0.034*	0.022**	1.48	0.0008**	0.000124	6.97
Rainfall	0.052**	0.017**	3.01	-0.007**	0.003027	-2.62
Trend	0.005**	0.002**	2.62	0.0008	0.003397	0.26
_cons	-0.008	0.114	-0.08	1.133**	0.106024	10.69
Log Likelihood	-539.168**			-1063.46**		
Wald Chi2	121.15**			143.08**		
AIC	1098.335			2146.913		
BIC	1144.483			2193.087		
No of Obs	748			748		

Table 7: Sorghum estimation result

	Cob douglas			Linear		
	Coef.	Std. Err.	Z	Coef.	Std. Err.	Z

Mean						
Heat index	-0.033**	0.006	-5.3	-0.003**	0.0006	-4.54
Rain index	-0.130**	0.051	-2.52	-8.8E-05	8.93E-05	-0.98
Rainfall	0.087**	0.069	1.26	-0.013**	0.004	-3.18
Trend	0.005**	0.003	1.83	0.007**	0.003	2.1
_cons	-0.157	0.452	-0.35	1.514**	0.115	13.13
Std, Dev.						
Heat index	0.004	0.004	0.99	0.0003	0.0005	0.62
Rain index	0.021	0.039	0.55	-0.001**	6.38E-05	-2.51
Rainfall	-0.199**	0.049	-3.99	-0.008**	0.002	-3.18
Trend	0.004*	0.002	1.96	0.005**	0.002	2.24
_cons	1.650	0.310	5.31	0.632**	0.078	8.09
Log Likelihood	-234.917**			-307.267**		
Wald Chi2	51.03**			48.41**		
AIC	489.8337			634.5349		
BIC	531.1893			675.8905		
No of Obs	462			462		

Table 8: Yam estimation result

	Cobb douglas			Linear		
	Coef.	Std. Err.	Z	Coef.	Std. Err.	Z
Mean						
Heat index	-0.023*	0.006	-3.37	0.031**	0.008112	3.83

Rain index	-0.024	0.042	-0.57	-0.022	0.033236	-0.68
Rainfall	-0.008	0.051	-0.15	0.229**	0.044737	5.13
Trend	0.0132**	0.003	4.49	-0.001	0.003302	-0.51
_cons	2.295**	0.344	6.66	-1.888**	0.281471	-6.71
Std Dev						
Heat index	-0.003	0.005	-0.73	0.003	0.005	0.7
Rain index	0.033	0.030	1.1	-0.032	0.023	-1.41
Rainfall	-0.041	0.044	-0.94	-0.097**	0.037	-2.57
Trend	0.006**	0.002**	3.21	0.007**	0.002	3.37
_cons	0.570**	0.283**	2.01	1.103**	0.229	4.81
Log Likelihood	-345.736**			-1946.08**		
Wald Chi2	30.79**			34.85**		
AIC	711.4715			3912.166		
BIC	755.1705			3956.035		
No of Obs	594			594		

Table 9: Cowpea estimation result

	Cobb douglass		
	Coef.	Std. Err.	Z
Mean			
Heat index	0.031**	0.008	3.83
Rain index	-0.022	0.033	-0.68
Rainfall	0.229**	0.044	5.13

Trend	-0.001	0.003	-0.51
_cons	-1.888**	0.281	-6.71
Std Dev			
Heat index	0.004	0.005597	0.7
Rain index	-0.032	0.023265	-1.41
Rainfall	-0.097**	0.037845	-2.57
Trend	0.007**	0.002	3.37
_cons	1.103**	0.229	4.81
Log Likelihood	-507.993**		
Wald Chi2	34.17**		
AIC	1035.986		
BIC	1080.848		
No of Obs	656		

Table 10: Maize estimation result

	Cob douglas			Linear		
	Coef.	Std. Err.	Z	Coef.	Std. Err.	Z
Mean						
Heat index	-0.010**	0.005	-2.04	0.307**	0.081	3.8
Rain index	-0.016	0.025	-0.63	0.046	0.048	0.97
Rainfall	0.040	0.045	0.89	-0.037	0.043	-0.86
Trend	0.007**	0.002	2.82	0.022**	0.004	5.08
_cons	0.178	0.306	0.58	-2.329**	0.528	-4.41

Std Dev						
Lh	0.019**	0.00404	4.7	-0.071	0.062811	-1.13
Lr	0.113**	0.017843	6.33	-0.027	0.035804	-0.77
Lrn	-0.162**	0.033712	-4.83	-0.072**	0.030663	-2.36
Trend	0.0124**	0.001362	9.17	-0.0008	0.00313	-0.27
_cons	1.179**	0.235673	5.01	1.345**	0.383785	3.51
Log Likelihood	-521.867**			-341.646**		
Wald Chi2	17.66**			49.66**		
AIC	1063.734			703.2921		
BIC	1110.467			743.9531		
No of Obs	791			791		

Table 11: Melon estimation result

	Cobb Douglas		
	Coef.	Std. Err.	Z
Mean			
Heat index	0.307**	0.081**	3.8
Rain index	0.0467	0.048	0.97
Rainfall	-0.037	0.043	-0.86
Trend	0.021**	0.0043**	5.08
_cons	-2.329**	0.527**	-4.41
Std Dev,			
Heat index	-0.071	0.062811	-1.13

Rain index	-0.027	0.035804	-0.77
Rainfall	-0.072**	0.030663	-2.36
Trend	-0.0008	0.00313	-0.27
_cons	1.345**	0.383	3.51
Log Likelihood	-341.646**		
Wald Chi2	49.66**		
AIC	703.2921		
BIC	743.9531		
No of Obs	431		