Zwick Center for Food and Resource Policy

Working Papers Series

No. 17

Groundnut Production and Climatic Variability: Evidence from Uganda

Aizhen Li, Boris E. Bravo-Ureta, David K. Okello,

Carl M. Deom, Naveen Puppala

February 2013

Charles J. Zwick Center for Food and Resource Policy
Department of Agricultural and Resource Economics
College of Agriculture and Natural Resources
1376 Storrs Road, Unit 4021
Storrs, CT 06269-4021
Phone: (860) 486-2836
Fax: (860) 486-1932
Contact: ZwickCenter@uconn.edu
www.zwickcenter.uconn.edu

Groundnut Production and Climatic Variability: Evidence from Uganda

Aizhen Li[1]
Boris E. Bravo-Ureta[2]
David K. Okello[3]
Carl M. Deom[4]
Naveen Puppala[5]

Abstract

This study contributes to understanding the relationship between climatic variables and groundnut production in different farming systems in Uganda. Alternative production function models are estimated using pooled cross-sectional time series data at the district level. The models incorporate land area, indicators for farming systems, technological change, and either rainfall or the El Niño–Southern Oscillation (ENSO) effect as variables to account for climatic conditions. The data set includes 333 observations corresponding to 37 districts for 9 consecutive years, from 1992 to 2000. Analyses were performed using a Translog functional form and GARCH estimators. The results suggest that the partial elasticity of production for land is positive, high and significant, which is consistent with a priori expectations. Farming systems are also found to have a significant impact on output variability. Climatic conditions, measured by rainfall, have a non-significant effect; but, when the ENSO phenomenon is used instead a significant negative effect is detected particularly for the warm phase. An important and alarming finding is a marked negative rate of technological change revealing productivity losses over the time period studied.

Keywords: Uganda; Groundnuts; Productivity; GARCH; Rainfall; ENSO

February 2013

---

[1] A. Li, was a Graduate Student in ARE, UConn, when this research was undertaken.

[2] B. E. Bravo-Ureta, Professor of Agricultural and Resource Economics and Economics, University of Connecticut (UConn) and Adjunct Professor of Agricultural Economics, University of Talca, Chile (**corresponding author**: boris.bravoureta@uconn.edu; 1376 Storrs Rd., Storrs, CT 06269-4021; phone: 860-486-1918; fax: 860-486-1932).

[3] D. K. Okello, Plant Breeder-Geneticist, National Semi-Arid Resources Research Institute (NaSARRI), Serere, Uganda.

[4] C. M. Deom, Professor, Plant Pathology, University of Georgia.

[5] N. Puppala, College Associate Professor, Agricultural Science Center at Clovis, New Mexico State University.

Groundnut Production and Climatic Variability: Evidence from Uganda

1. Introduction

Agriculture in Africa has a crucial role to play in spurring growth, overcoming poverty, and enhancing food security (World Bank, 2008). Growth in agriculture can be compatible with development patterns that are employment-intensive and hence favorable to the poor (FAAP, 2006). As an economic activity, agriculture can be a source of growth for the national economy, a provider of investment opportunities for the private sector, and a prime driver of agriculture-related industries and the rural nonfarm economy. The sector accounts for a large share of national income, employment, and foreign trade in Africa. However, the persistent underperformance of farming in much of Africa has not helped significantly to reduce poverty or to alleviate hunger and malnutrition. In order to achieve higher rates of agricultural growth, farm productivity needs to improve significantly (FAAP, 2006; World Bank, 2008).

A growing scientific literature has established empirically that climatic conditions have a measurable impact on agricultural output and productivity. Winter et al. (1996) studied the expected impact of climate on macroeconomic variables, household income, and food consumption in Africa, Asia, and Latin America, and concluded that Africa was the most vulnerable of the areas studied. Jones et al. (1997) suggested that climate change has a direct effect on crop yields and farm management, and that variations in these parameters will have subsequent effects on the implementation of new economic policies and adaptation strategies. According to Masters and Wiebe (2000), the most direct impact of climate change in Africa stems from growing water shortages or drought, leading to an increasing dependence on imported foodstuffs (Boubacar, 2010). A recent IPCC report (Boko et al., 2007) concluded that changing climatic conditions are likely to impose additional pressure on water availability, reducing the length of the growing season and forcing large regions of marginal agriculture out of production. The same report predicts a 50% reduction in yields by 2020 and a 90% reduction in crop net revenues by 2100 in areas that are already classified as marginal in Africa.

Various modeling frameworks have been used to estimate the impact of changing climatic conditions on the economy in general and the agricultural sector in particular. One such framework is based on simulation methods and includes work by Mearns et al. (1997), Phillips et al. (1998), Aggarwal and Mall (2002), and Wang (2005). A second option that has been widely used by economists is the Ricardian approach, in which regression analysis is used to examine the impact of climatic conditions on land values or net farm income (e.g., Mendelsohn et al., 1994; Deschenes and Greenstone, 2007). A third modeling alternative relies on regression estimates of production functions where changes in aggregate or specific outputs are explained in terms of a set of variables that includes climatic indicators (e.g., Austin et al., 1998; Chen et al., 2004; Barrios et al., 2008; Schlenker and Lobell, 2010). This latter modeling approach is applied in this study, consistent with the type of data utilized.

As Hassan (2010) has recently noted, given the vulnerability of African countries to global warming, more disaggregated studies—in terms of geography, agroecological zones and type of farming—of the impact of climatic change on agriculture are needed. Moreover, the African Centre for Technology Studies (ACTS) has concluded that agriculture in Uganda is highly susceptible to changes in climatic conditions, and the most important factor limiting productivity is precipitation (Orindi and Eriksen, 2005). Considering the dearth of studies that examine the relationship between climatic conditions and agricultural productivity in Uganda, this constitutes an important subject for research to support strategic adaptations to increasing climatic variability.

This paper aims at narrowing this knowledge gap by assessing the impact of climatic variability on groundnut production in Uganda, accounting for the various farming systems found throughout the country. The focus on groundnuts is based on the importance of this crop to the country, as detailed in the next section. Alternative production function models are estimated, using data for 13 farming systems in 37 districts for the period 1992–2000. Climatic variability is captured in two alternative ways: (1) using rainfall data; and (2) using the phases of the El Niño–Southern Oscillation (ENSO). The data available for rainfall is limited, as elaborated below, and this provides the major rationale for using the ENSO phases. The estimation strategy takes into account the panel structure of the data by using the Generalized Autoregressive Conditional Heteroscedastic (GARCH) method.

The remainder of this paper consists of six sections. Section 2 is an overview of Ugandan agriculture and groundnut production, and Section 3 is a review of the existing literature on the connection between rainfall and agricultural productivity. Sections 4 and 5 present the characteristics of the data and the methodology, respectively. Section 6 discusses the results and the last section presents our conclusions.

2. Overview of Ugandan Agriculture and Groundnut Production

Uganda is a landlocked country in eastern Africa (Figure 1) covering an area of about 241,000 km^2. The total population was estimated at 25,827,000 in 2003, with an expected annual growth rate of 3.24% for 2000–2005 (UN, 2008). Most of Uganda has a tropical climate, with two rainy and two dry seasons per year. The rainy seasons are from March to May and from September to November (Howard, 1991). The country is divided into several broad agroecological zones based on the similarity of various characteristics within each zone including soil type, production potential, topography, temperature, rainfall, and farming practices (Sandra, 1998).

In the recent World Bank (2008) classification, Uganda is included as an agriculture-based country, which means that the farming sector plays a dominant role in the country's economy. This classification is consistent with the fact that agriculture accounts for 36% of GDP, 81% of the employed labor force, and 31% of export earnings. The total area under cultivation is just over 68,000 km^2, or about one-third of the land area, and about

70% of this area is used to produce food crops for local consumption (Encyclopedia of the Nations, Uganda, 2007).

Groundnut is the second most widely grown legume in Uganda, after common beans. Groundnuts were brought into Uganda by early traders and travelers following the initial introduction of this crop into East Africa by Portuguese explorers in the mid-1800s (Nalyongo and Emeetai-Areke, 1987; Busolo-Bulafu, 1990). It is considered a women's crop, since it was originally grown by females to supplement family diets with protein (Kenny and Finn, 2004). The groundnuts are consumed primarily roasted or as oil. This crop requires few inputs and increases soil fertility by fixing nitrogen, making it an appropriate choice in the low-input agricultural systems that are prevalent among many small-scale farmers in Africa (Smartt, 1994; Okello et al., 2010). Moreover, as a cash crop, groundnut can give relatively high returns for a limited land area, and is well adapted to the hot semi-arid conditions characterizing many of the regions where it is grown (Wangai et al., 2001).

Groundnut yields in Uganda are constrained by various factors. One constraint is the high incidence of diseases and pests where groundnut rosette disease (GRD) and late leaf spot (LLD) are the main culprits (Okello et al, 2010). Bonabana-Wabbi et al. (2008) noted that GRD and LLD on groundnut can lead to complete crop failure, and farmers have limited access to operating capital to purchase chemical pesticides or fungicides to cope with infestations. Other significant constraints include restricted supplies of improved seed varieties and unreliable rainfall, with recurring droughts being a major challenge (Busolo-Bulafu, 1990; Naidu et al. 1999; Okello et al., 2010).

3. Rainfall and Agriculture: Literature Review

As already noted, a number of researchers have suggested the importance of rainfall for general economic growth in Africa. Tesfaye (1988) and Tsegay (1998) used different methodologies to predict the impact of rainfall patterns on production in Ethiopia. More detailed studies examined the correlation between yields and the amount of rainfall for particular crops in a given year. The study by Austin et al. (1998) in Spain showed a strong correlation between farm-specific yields and rainfall. O'Connell and Ndulu (2000) included a measure of the number of dry years in a cross-country growth regression of African countries and found that this variable has a significant negative effect on economic growth rates.

Using climate data from the Intergovernmental Panel on Climate Change (IPCC), Masters and Sachs (2001) showed the effects of rainfall on a sample of developing and developed countries. Another early contribution to this literature is by Sherlund et al. (2002) who incorporated rainfall, soil fertility, and slope into a stochastic production frontier model for rice in the Côte d'Ivoire. More recently, Alem et al. (2010), using random effects Tobit adoption models and panel data from a sample of producers located in the Central Highlands of Ethiopia, concluded that increased rainfall in the previous year is associated with greater fertilizer applications in the current year, while higher rainfall variability leads to a lower probability of using fertilizer and also decreases the intensity of fertilizer use. These results imply that the connection between good weather along with lower rainfall variability and the use of fertilizer has a significant effect on productivity and farm investments. Schlenker and Lobell (2010) estimated the impact of climatic variability, including temperature and precipitation, on yield of maize, sorghum, millet, groundnut, and cassava in several sub-Saharan African countries. The only non-climatic variables in their model are production and land.

The usefulness of rainfall analysis as part of an early warning system has gained support in some developing countries. Tsegay (1998) showed the importance of rainfall and drought patterns in the development of an early warning system in the case of Ethiopia. Lemi (2005) used time series econometric models and data from five provinces in Ethiopia from 1954 to 1994, to analyze the dynamic link between rainfall and yields by province and crop type. Lemi's work, like other similar studies, was limited by the paucity of available information on other factors involved in the relationship between rainfall and yields, such as availability and access to other farm inputs, land quality, government agricultural policy, and infrastructure. Unlike rainfall, these factors can be controlled or manipulated by farmers or governments in the short and/or the long term.

An alternative to using rainfall data, which can be difficult to obtain in Africa, is to rely on information concerning the El Niño/La Niña–Southern Oscillation, or ENSO, climatic pattern. ENSO is a general term used to describe both warm (El Niño) and cool (La Niña) ocean–atmosphere events in the tropical Pacific. El Niño events, in which sea surface temperatures (SST) in the eastern equatorial Pacific Ocean are anomalously warm, occur on average one to two times a decade. When SSTs are anomalously cool, the event is called La Niña (Trenberth and Hoar, 1996; Rajagopalan et al., 1997). The ENSO events have significant effects on precipitation levels around the globe (Ubilava, 2012).

In his study of the cause and characteristics of drought in Ethiopia, Tesfaye (1988) showed that there was a high correlation between the annual rainfall series and ENSO events. El Niño events have been associated with low grain yields in south Asia and Australia and high grain yields in the North American prairies (Garnett and Khandekar, 1992). Recently Ubilava (2012), using an autoregressive approach, found that the ENSO events have an important impact on coffee supplies and thus a statistically significant effect on world coffee prices. Moreover, the author determined that the impact of La Niña and El Niño varies geographically depending on the type of coffee (robusta vs. arabica) that dominates in the various growing regions.

In summary, the effect of growing climatic variability on agricultural productivity in Africa has been well established. However, analyses for specific crops and countries are limited in general, and for groundnuts in Uganda in particular. Therefore, in this paper we analyze the effect of climatic variability based alternatively on precipitation levels and the ENSO phases on groundnut production using data for 37 districts in Uganda.

4. Data Description

Data on groundnut production, land area devoted to groundnut production, and rainfall were obtained from the National Semi-Arid Resources Research Institute located in Serere, Uganda (NARO, 2010; MLWNR, 2010). The ENSO information was obtained from the Center for Ocean Atmospheric Prediction Studies (COAPS). The total number of observations available for the analysis is 333, corresponding to 37 districts in Uganda, each observed for 9 consecutive years from 1992 to 2000. These districts are distributed over 13 farming systems. The output variable is total annual groundnut production per district (*Q*) in tons. The explanatory variables are: land area in hectares devoted to groundnut in each district in each year (*L*); a set of binary variables denoting the farming system (*FS*) (agroecological fixed effects); rainfall in each district in the 11-month period from February to December measured in mm (*R*), alternatively binary variables to capture the ENSO effect; and technological change measured as a time trend (*T*) or as a set of year dummy variables (*TD*) (time fixed effects), which are commonly used alternatives in the economics literature (Ahmad and Bravo-Ureta, 1996). The farming systems correspond to different agroecological zones with a distinct natural resource base, climate, location, and altitude. A summary of descriptive statistics is given in Table 1, and a summary of the farming systems and corresponding districts is provided in Table 2.

The ENSO effect, used as an alternative to the rainfall variable, is defined according to the COAPS classification as follows: “La Niña”, the colder and dryer phase (*CP*); “El Niño”, the warmer and wetter phase (*WP*); or neutral, which is the omitted category in the models below. The period of analysis covered in this study includes one WP year (1997) and two CP years (1998 and 1999), while the other six years (1992–1996 and 2000) are neutral.

The rainfall data were obtained either directly or indirectly through imputation. There are 37 districts in Uganda, and 13 meteorological stations covering the whole country. Nine of the 37 districts had local meteorological stations that made direct measurements of rainfall data. The other 28 districts did not have recorded rainfall information, and rainfall data were imputed whenever possible. For this purpose, we assume that if two districts share the same meteorological station, they will also have similar rainfall. Under this assumption, it was possible to impute rainfall data based on information from neighboring districts sharing the same station for 18 out of the 28 districts. However, there were five stations covering the remaining 10 districts for which rainfall data were not obtainable and thus no imputation was possible. Thus, rainfall information is available for 195 out of the total 333 observations in the data set. This significant gap in the number of observations is the major rationale for using the ENSO phase as an alternative to rainfall data, which makes it possible to include all data points. Table 2 details the presence of meteorological stations in the various farming systems and districts throughout Uganda, and Figure 2 summarizes the districts with and without rainfall data and the stations from which precipitation data were available.

5. Methodology

This study utilizes a Translog production function framework to examine the relationship between groundnut production and rainfall based on the variables discussed above. The Translog (*TL*) is a flexible functional form, which can be interpreted as a second-order approximation to an unknown technology (Christensen et al., 1971). In empirical analysis it is customary to express all variables as deviations from their geometric mean. An advantage of such transformation is that the estimated first-order parameters can be interpreted directly as partial elasticities of production at the sample geometric mean (Coelli et al., 2005). In our particular model specification, this transformation is applied to groundnut production (*Q*), land area (*L*), and rainfall (*R*).

Given that climatic conditions and technological progress are modeled using alternative specifications, we estimate several models, all of which include land area (L) and the set of Farming Systems dummies (*FS*). Unfortunately, the lack of data makes it impossible to include in the production function conventional inputs beyond land area (L). However, our specification is similar in this respect to the production function estimates recently published by Schlenker and Lobell (2010) and Lemi (2005).

The first model is what we referred to as the base, or Model 1, and is given by:

Model 1:

$$lnQ = \alpha_0 + \alpha_L lnL + \lambda T + \frac{1}{2}\beta_{LL}(lnL)^2 + \frac{1}{2}\gamma_{TT}T^2 + \gamma_{LT}(lnL)T + \sum \delta FS + \varepsilon \qquad (1)$$

where all variables are as defined earlier, ε is the error term, and the other Greek letters are parameters to be estimated. Thus, Model 1 incorporates technological progress as a time trend, and no rainfall effect is included.

Next, we consider the rainfall effect by incorporating the continuous rainfall variable (*R*) in Model 1, giving rise to Model 2:

Model 2:

$$lnQ = \alpha_0 + \alpha_L lnL + \alpha_R lnR + \lambda T + \frac{1}{2}\beta_{LL}(lnL)^2 + \frac{1}{2}\beta_{RR}(lnR)^2 + \frac{1}{2}\gamma_{TT}T^2 + \beta_{LR}(lnL)(lnR) + \gamma_{LT}(lnL)T + \gamma_{RT}(lnR)T + \sum \delta FS + \varepsilon \qquad (2)$$

As indicated above, the rainfall data is incomplete, so we can only include 195 observations. Alternatively, we substitute the ENSO dummy variables *CP* and *WP* for *R*, and we define Model 3 as:

Model 3:

$$lnQ = \alpha_0 + \alpha_L lnL + \lambda T + \frac{1}{2}\beta_{LL}(lnL)^2 + \frac{1}{2}\gamma_{TT}T^2 + \gamma_{LT}(lnL)T + \theta_{CP}CP + \theta_{WP}WP + \sum \delta FS + \varepsilon \qquad (3)$$

where *CP* is equal to 1 for the cold phase and 0 otherwise; *WP* is equal to 1 for the warm phase and 0 otherwise; and the omitted category is the neutral phase. For simplicity we use the same Greek letters to stand for the coefficients for the same variables in all three models, but clearly this does not imply that the estimated parameters are expected to have the same values.

A useful feature of the TL functional form is that it reduces to a Cobb–Douglas if the βs and γs in models (1) – (3) are equal to zero (Coelli et al., 2005). In other words, the Cobb–Douglas (CD), which is nested within the TL, can be obtained by setting
$\beta_{LL} = \beta_{RR} = \gamma_{LT} = \gamma_{RT} = \gamma_{TT} = 0$

Note that the specific terms set to zero do vary with the model. Therefore, the CD models corresponding to equations (1), (2), and (3), respectively, can be written as:

Model 4: $$lnQ = \alpha_0 + \alpha_L lnL + \lambda T + \sum \delta FS + \varepsilon \quad (4)$$

Model 5: $$lnQ = \alpha_0 + \alpha_L lnL + \alpha_R lnR + \lambda T + \sum \delta FS + \varepsilon \quad (5)$$

Model 6: $$lnQ = \alpha_0 + \alpha_L lnL + \lambda T + \theta_{CP} CP + \theta_{WP} WP + \sum \delta FS + \varepsilon \quad (6)$$

To compare formally the TL models (models 1–3) with the restricted CD counterparts (models 4–6), the following F-statistic is computed:

$$F = \frac{(\tau - 1)(n - k)}{k_2}$$

where $\tau = RRSS/URSS$; $RRSS$ is the residual sum of squares for the restricted model; $URSS$ is the residual sum of squares for the unrestricted model; n is the number of observations; k is the number of total regressors; and k_2 is the difference between the of number of parameters in the unrestricted and restricted models (Coelli et al., 2005).

Models (1) – (6) treat technological change as a continuous trend, which may be too restrictive. Alternatively, we use annual dummy variables (*TD*), where 1992 is the excluded year, resulting in the following alternative models:

Model 7-12: $$lnQ = \alpha_0 + \alpha_L lnL + \frac{1}{2}\beta_{LL}(lnL)^2 + \sum \delta FS + \sum \lambda TD + \varepsilon \quad (7)$$

$$lnQ = \alpha_0 + \alpha_L lnL + \alpha_R lnR + \frac{1}{2}\beta_{LL}(lnL)^2 + \frac{1}{2}\beta_{RR}(lnR)^2 + \beta_{LT}(lnL)(lnR) + \sum \delta FS + \sum \lambda TD + \varepsilon \quad (8)$$

$$lnQ = \alpha_0 + \alpha_L lnL + \frac{1}{2}\beta_{LL}(lnL)^2 + \theta_{CP} CP + \theta_{WP} WP + \sum \delta FS + \sum \lambda TD + \varepsilon \quad (9)$$

$$lnQ = \alpha_0 + \alpha_L lnL + \sum \delta FS + \sum \lambda TD + \varepsilon \quad (10)$$

$$lnQ = \alpha_0 + \alpha_L lnL + \alpha_R lnR + \sum \delta FS + \sum \lambda TD + \varepsilon \quad (11)$$

$$lnQ = \alpha_0 + \alpha_L lnL + \theta_{CP} CP + \theta_{WP} WP + \sum \delta FS + \sum \lambda TD + \varepsilon \quad (12)$$

Models (7), (8) and (9) are TL models, while models (10), (11) and (12) are the corresponding CD specifications. Models (7) and (10) correspond to TL and CD versions of the base model, respectively, where technological change is incorporated using time dummies (*TD*). Models (8) and (11) include rainfall (*R*) along with *TD*, while models (9) and (12) use the ENSO dummy variables to replace rainfall (*R*). The excluded category for ENSO is the neutral phase.

The estimation strategy adopted recognizes that Ordinary Least Squares (OLS) regressions, which have been widely used to estimate production functions, assume that the error term is homoscedastic. However, heteroscedasticity tends to be a common problem with cross-sectional data (Rao, 1970). Even in the presence of heteroscedasticity, OLS models give unbiased parameters, but the standard errors are biased, and so are the results of hypothesis testing. Several tests have been developed to determine if the variance of the error terms in a regression model is constant or not, such as the White, Breusch–Pagan, Portmanteau Q and Lagrange-Multiplier (LM) tests (White, 1980; Breusch and Pagan, 1979; McLeod and Li, 1983; Engle, 1982). The fact that the data used in this study are also time-series in nature poses the possibility of autocorrelation, i.e., that errors are not independent through time. If the error term is autocorrelated, OLS estimates again are unbiased, but not efficient (Greene, 2008). Given the cross-sectional time series data used here, we adopted the ARCH/GARCH (Autoregressive Conditional Heteroscedastic/Generalized Autoregressive Conditional Heteroscedastic) modeling framework developed by Engle (1982) and refined by Bollerslev (1986) as a way to deal with both heteroscedasticity and autocorrelation. The basic idea behind ARCH is that the variance of the error term at time *t* depends on the size of the squared error terms in previous time periods (Engle, 1982). A very useful generalization of ARCH is the GARCH method, introduced by Bollerslev (1986), which also features a weighted average of past squared residuals. In this method, the weights decline but never go completely to zero (Engle, 2001). The GARCH approach is more flexible, and consequently it is the option we adopt in our analysis. Our GARCH regression model can be written as:

$$y_t = x_t'\beta + \varepsilon_t \tag{13}$$

$$\varepsilon_t = \epsilon_t - \varphi_1\varepsilon_{t-1} \tag{14}$$

$$\epsilon_t = h_t e_t \tag{15}$$

$$h_t^2 = \omega + \sigma\epsilon_{t-1}^2 + \gamma h_{t-1}^2 \tag{16}$$

where ω, σ and γ are positive parameters, and $e_t \sim iid(0,1)$. The unit variance assumption for e_t ensures that h_t^2 is the variance of e_t. Equations (13) – (16) combine the first-order autoregressive error model with the GARCH (1, 1) variance model; this combination is denoted as AR (1)-GARCH (1, 1). For the GARCH (1, 1) model, the first number refers to the number of autoregressive lags, also called ARCH terms, while the second number refers to how many moving average lags are specified, often referred to as the number of GARCH terms (Engle, 2001).

Examples of applications of GARCH in agriculture include the work of Aradhyula and Holt (1988), who utilized this framework in their analysis of meat retail prices during the 1970s and early 1980s and found it to be a suitable approach for their data. Yang et al. (1992) examined alternative models that correct for heteroscedasticity in wheat yields and concluded that the GARCH specification is promising, particularly when the source of heteroscedasticity cannot be identified.

6. Results

Initially, all 12 models (equations 1–12) presented above were estimated using both OLS and GARCH procedures. After several tests, the TL models estimated with the GARCH method, the results of which are shown in Tables 4 and 5, were retained for further analysis.

The first step was to test the CD models against the TL models using the F-statistic described earlier. The values of the F-statistics for both OLS and GARCH models are given in Table 3. The results indicate that in all cases, the F-tests are significant, favoring the TL functional form instead of the simpler CD models. Therefore, all analyses reported below are based on the TL models.

As already discussed, OLS assumes homoscedasticity and no autocorrelation, and both of these assumptions are subject to statistical testing. If the assumptions for the OLS models are rejected, then the GARCH method is used to correct for heteroscedasticity and/or autocorrelation. Based on both the Portmanteau Q and the Lagrange Multiplier (LM) tests, heteroscedasticity is strongly rejected in the TL time-trend base model (Model 1), the time-trend rainfall model (Model 2), and the time-dummy rainfall model (Model 8) for all lag windows. To diagnose autocorrelation, the generalized Durbin–Watson (DW) statistic is used, and the results support the presence of autocorrelation for all TL time-trend and time-dummy models (Models 1–3 and 7–9). Overall, Models 1, 2, and 8 fit an AR(1)-GARCH(1, 1) structure, while the time-trend ENSO model (Model 3), the time-dummy base model (Model 7) and the time-dummy ENSO model (Model 9) do not exhibit heteroscedasticity, and AR(1) was sufficient for correction.

Consistent with the outcomes of the tests for functional form, homoscedasticity, and autocorrelation, we present the results for the TL models estimated with GARCH. Table 4 presents the parameter estimates for the base (Model 1), the rainfall (Model 2) and the ENSO (Model 3) models when technological change is treated as a time trend. By contrast, Table 5 shows the same sequence of models when time is incorporated as a set of dummies (Models 7, 8 and 9).[1]

In all six models, the linear parameters for land (*L*) are significant and slightly less than 1.0; that is, output is roughly proportional to the land area at the geometric mean. However, the parameter for L^2 is significant and negative, which indicates a decreasing rate in output growth as land area increases. The parameters for farming systems (*FS*) are

[1] For comparative purposes, we also show the counterpart for Models (3) and (9) estimated via OLS in Table 4 and 5, respectively.

almost all negative and significant (1%) in the base and ENSO models, regardless of whether we treat time as discrete or continuous. However, when we include the rainfall variable in the model, most of the farming system parameters lose significance. For example, in the model incorporating the time-trend and rainfall variables (Table 4, Model 2), the coefficients for all the farming systems but three (*FS*1, *FS*10 and *FS*12) are nonsignificant.

The parameters for technical change (*T*) are consistently significant in the time-trend base and ENSO models (Table 4, Models 1 and 3). By comparison, most of the parameters for the time-dummy variables are negative and significant except for *TD*2, which has a positive and significant coefficient (Table 5, Models 7, 8, and 9). In addition, in the models including rainfall (Table 4, Model 2; and Table 5, Model 8), the parameters for this variable are not significant in either the time-dummy or the time-trend models. The coefficients for warm ENSO (*WP*) are negative in all corresponding models. By contrast, the coefficient for the cold ENSO (*CP*) is significant and positive in the time-trend equation (Model 3) but negative and significant in the time-dummy model (Model 9).

Tables 4 and 5 also show the F-statistics used to compare the base models versus the alternative specifications (ENSO or rainfall), which is a test of the null hypothesis that all ENSO (*CP* and *WP*) or rainfall parameters are zero. The results show that the time-trend with rainfall model (Model 2) is not a significant improvement over the base model (Model 1), whereas the rainfall with time-dummies model (Model 8) is a significant improvement over the base model (Model 7). On the other hand, both ENSO models (Models 3 and 9) are significantly better (F-statistic is significant at the 1%) than the corresponding base models (Models 1 and 7).

It is tempting to conclude that the ENSO models are preferred to either the base models or rainfall models; however, since the data sets for the rainfall and ENSO models are different due to missing values in the former, further analysis with additional data is needed to come to a more definitive conclusion as to which specification is preferable. Nevertheless, Tables 3, 4, and 5 reveal that the most robust results are associated with the TL functional form that includes the ENSO variable to capture climatic conditions estimated with the GARCH procedure. Moreover, technological change seems to be captured better by the more flexible option of using time dummies rather than by a time trend. A remarkable and consistent finding is that technological change, regardless of the model used, is negative and significant, pointing to technological regress or a decline in production, *ceteris paribus*, over the time period covered by the data.

Based on the above discussion, the most robust model appears to be TL with time dummies and the ENSO events (Model 9), and we rely on those results for some additional analysis. First, to investigate further the robustness of Model 9, we tested the following two null hypotheses: (1) all *FS* parameters are jointly equal to zero; and (2) all *TD* parameters are jointly equal to zero. The F-statistics obtained for both cases (43.32 for *FS*, and 187.22 for *TD*) lead to a strong rejection of both null hypotheses. The coefficients of the *TD* variables in Model 9, which capture technical change, are positive and significant for only one (*TD*2) of the six estimates, while the other five are negative and significant. Also note that parameters for *TD*6 and *TD*7 cannot be estimated, because 1997 (*TD*6 = 1) is a warm year and 1998 (*TD*7 = 1) is a cold year; therefore, *TD*6 and *TD*7 are equivalent to the *WP* and *CP* variables, respectively, so separate parameters cannot be identified.

Following Cuesta (2000), year-to-year technical change is given by the difference between the coefficients of two time dummies, as denoted by the following equation:

$$TC_{t,t+1} = \lambda_{t+1} - \lambda_t \qquad (17)$$

which reflects the rate of technical change between two consecutive years (t and t+1). As already noted, technical change between 1992 and 2000 was negative, signaling the presence of technological regress, i. e., a loss in productivity, over the years analyzed. Year-to-year rates of technical change are: 2.5% for 1992–1993; -8.5% for 1993–1994; -0.10% for 1994–1995; -15.7% for 1995–1996; and -21.6% for 1999–2000. The cumulative technical change between 1992 and 2000 is the coefficient for the last time dummy, i. e., around -23%, and the average over the nine-year period would be -2.6%. These negative results suggest that major efforts would be required to reverse this rate of productivity decline.

For farming systems, the largest coefficient is 0.12 (*FS1* and *FS2*), while the lowest is -0.14 (*FS8*), revealing considerable output variability across agroecological zones in Uganda. On the other hand, the coefficients for the ENSO dummies are -0.13 for *CP* and -.54 for *WP*, indicating that shifts from the neutral phase have significant negative effects on output, particularly during the warm phase.

7. Concluding Remarks

This study analyzes the relationship between groundnut output and land area, along with climatic conditions, for 13 different farming systems, while accounting for technological progress using various production function specifications. The model chosen for a more detailed analysis is a translog that captures climatic conditions through dummy variables that account for the El Niño–Southern Oscillation (ENSO) phases, while technological change is modeled using year dummies (time-fixed effects). The data comprise a pooled cross-sectional time series covering 37 Ugandan districts over a period of 9 years (1992-2000). Given the pooled nature of the data, heteroscedasticity and autocorrelation are dealt with by using the GARCH modeling approach.

The results indicate that climatic effects expressed in the production function as rainfall variability have a nonsignificant effect on groundnut output. By contrast, the cold and warm ENSO phases have a negative and significant effect on output relative to the neutral phase, with the warm phase having a greater effect. A key finding that raises considerable concern is that technological change is found to be regressive over the time period included in the analysis; this is a robust result that emerges from all models examined. Concerns regarding low and even negative rates of technological change in African agriculture have been reported by other authors, including Nkamleu (2004), Fulginiti et al. (2004), Avila and Evenson (2010), and Rezek et al. (2011). It is encouraging to note, however, that new evidence is signaling a shift toward productivity gains among farmers in Africa (Binswanger-Mkhize and McCalla, 2010)

It is important to note that the authors made a major effort to compile the data set utilized in this paper; nevertheless, the time series available is short, which poses limitations on the analysis. Also, the lack of specific crop output data suitable for matching with climatic information prevents detailed analyses. Given the potentially profound effects that climate change might have on farming systems in Uganda, it is important that appropriate data sets be developed so that policy makers can have access to analyses based on more detailed information.

Although not a direct focus of this paper, an important strategy would be to redouble efforts focusing on improving seed varieties of groundnuts and other key crops in order to reverse the decline in productivity as well as to facilitate the adaptation to climate change. Such work needs to pay particular attention to the development and promotion of seed varieties that are suitable for specific agroecological zones. Moreover, a recent paper by Kassie et al. (2011) has clearly shown the positive effect that improved groundnut varieties can have on household income and poverty alleviation in rural Uganda. These authors also emphasize the importance of policies designed to facilitate the adoption of the improved material.

Finally, drawing from a recent analysis by Kato et al. (2011) for five regions in Ethiopia, it is important to highlight the role of water and soil conservation technologies in counteracting the effects of climate change on farming. In particular, Kato and colleagues find that soil and water conservation can have important benefits in moderating the effects of both high and low rainfall patterns, but such benefits can vary significantly across agroecological zones and because of the interaction among technologies. In sum, the evidence from Ethiopia clearly suggests that policy actions need to focus on technology packages, rather than individual technologies, and that, considering the geographic heterogeneity across Uganda, these packages need to be developed and targeted locally.

Acknowledgments
The study was partially supported by the United States Agency for International Development (USAID) under the Peanut CRSP Grant ECG-A-00-07-00001-00 2007-2012. The authors are grateful to Genti Kostandini for his helpful suggestions and to Carrie Crompton for her editorial assistance.

References

Aggarwal, P. K., Mall, R. K., 2002. Climate change and rice yields in diverse agro-environment of India: Effects of uncertainties in scenarios and crop models on impact assessment. *Clim. Chang*. 52, 331–343.

Ahmad, M., Bravo-Ureta, B. E., 1996. Dairy farm technical efficiency measures using panel data and alternative model specifications. *J. Product. Anal*. 7, 399–415.

Alem, Y., Bezabih, M., Kassie, M., Zikhali, P. Does fertilizer use respond to rainfall variability? Panel data evidence from Ethiopia. *Agric. Econ.* 41 (2010) 165–175.

Aradhyula, S.V.,Holt, M., 1988. GARCH time-series models: An application to retail livestock prices. *West. J. Agric. Econ*. 13, 365–74.

Austin, R. B., Martinez, C. C., Arrue, J. L., Playan, E., Cano-Marcellan, P., 1998. Yield-rainfall relationships in cereal cropping systems in the Ebro river valley of Spain. *Eur. J. Agron*. 8, 239–248.

Avila, A. and Evenson, R., 2010. Total factor productivity growth in agriculture: The role of technological capital, in R. E. Evenson and P. Pingali, eds., Handbook of Agricultural Economics, Vol. 4, Amsterdam: Elsevier Science, 3769–3822.

Barrios, S., Ouattara, B., Strobl, E., 2008. The impact of climatic change on agricultural production: Is it different for Africa? *Food Policy*, 33(4), 287–298.

Binswanger-Mkhize, H., McCalla, A. F., 2010. The changing context and prospects for agricultural and rural development in Africa. Chapter 70, in R. E. Evenson and P. Pingali, eds., Handbook of Agricultural Economics, Vol. 4, Amsterdam: Elsevier Science, 3573–3712.

Boko, M., I. Niang, A. Nyong, Vogel, C., Githeko, A., Medany, M., Osman-Elasha, B., Tabo, R., Yanda, P., 2007. Africa. Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, M. L. Parry, O. F. Canziani, J. P., Palutikof, P. J. van der Linden and C. E. Hanson, eds., Cambridge University Press, Cambridge UK, 433–467. http://www.ipcc.ch/pdf/assessment-report/ar4/wg2/ar4-wg2-chapter9.pdf

Bollerslev, T., 1986. Generalized autoregressive conditional heteroscedasticity. *J. Econom.* 31, 307–327.

Bonabana-Wabbi, J., Taylor, B., 2008. Health and environmental benefits of reduced pesticide use in Uganda: An experimental economics analysis. Paper presented at the joint annual meeting of the American Agricultural Economics Association and the American Council on Consumer Interests in Orlando, Florida, July 27–29.

Boubacar, I., 2010. The effects of drought on crop yields and yield variability in Sahel. Selected paper prepared for presentation at the Southern Agricultural Economics Association Annual Meeting, Orlando, FL, February 6–9.

Breusch, T. S., Pagan, A. R., 1979. Simple test for heteroscedasticity and random coefficient variation. *Econom.* 47, 1287–1294.

Busolo-Bulafu, C. M., 1990. Groundnut improvement program in Uganda. Fourth Regional Groundnut Workshop for Southern Africa, Arusha, Tanzania. ICRISAT , 55–59.

Chen, C., McCarl, B. A., Schimmelpfennig, D. E., 2004. Yield variability as influenced by climate: A statistical investigation. *Clim. Chang.* 66, 239–261.

Christensen, L., Jorgenson, D., Lau, L., 1971. Conjugate duality and the transcendental logarithmic production function. *Econom.* 4, 255–256.

COAPS (Center for Ocean-Atmospheric Prediction Studies) http://www.coaps.fsu.edu/jma.shtml

Coelli, T., Rao, P., O'Donnell, C., Battese, G., 2005 An Introduction to Efficiency and Productivity Analaysis, second ed., Springer, the United States of America.

Cuesta, R. A., 2000. A production model with firm-specific temporal variation in technical inefficiency: With application to Spanish dairy farms. *J. Product. Anal.* 13, 139–158.

Deschenes, O., Greenstone, M., 2007. The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather. *Amer. Econ Rev.* 97, 354-385.

Encyclopedia of the Nations, Uganda. 2007. http://www.nationsencyclopedia.com/Africa/Uganda-AGRICULTURE.html

Engle, R. F., 1982. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econom.* 50, 987–1007.

Engle, R. F., 2001. GARCH 101: The use of ARCH/GARCH models in applied econometrics. *J. Econ. Perspect.* 15, 157–168.

FAAP, 2006. Framework for African agricultural productivity. Forum for Agricultural Research in Africa, Accra, Ghana.

Fulginiti, L., Perrin, R. and Yu, B., 2004. Institutions and agricultural productivity in sub-Saharan Africa. *Agric. Econ.* 31, 169–180.

Garnett, E. R., Khandekar, M. L., 1992. The impact of large-scale atmospheric circulations and anomalies on Indian monsoon droughts and floods and on world grain yields: A statistical analysis. *Agric. For. Meteorol.* 61, 113–128.

Greene, W., 2008. Econometric Analysis sixth ed., Pearson, Prentice Hall.

Hassan, R. M., 2010. Implications of climate change for agricultural sector performance in Africa: Policy change and research agenda. *J. Afr. Econ.* 19, 77–105.

Howard, P. C., 1991. Nature Conservation in Uganda's Tropical Forest Reserves, IUCN Conservation Library, Gland, Switzerland.

Jones, J. W., Pickering N. B., Rosenzweig C., Boote, K.J., 1997. Simulated impacts of global change on crops. Technical Bulletin No. 100, University of Florida, Gainsville, Florida. 411–434.

Kato, E., C. Ringler, Yesuf, M., Bryan, E.., 2011, Soil and water conservation technologies: A buffer against production risk in the face of climate change? Insights from the Nile basin in Ethiopia. *Agric. Econ.* 42: 593–604.

Kassie, M., Shiferaw, B., Muri, G., 2011. Agricultural technology, crop income, and poverty alleviation in Uganda. *World Dev.* 39/10, 1784–1795.

Kenny, A. and Finn, K., 2004. Women, groundnuts (peanuts), and development in West Africa. http://forest.mtu.edu/pcforestry/resources/studentprojects/groundnut.html

Lemi, A., 2005. Rainfall probability and agricultural yield in Ethiopia. *East. Afr. Soc. Sci. Res. Rev.* Project MUSE. 57–96.

Masters, W. A., Sachs, J., 2001. Climate and development. Paper presented at the annual meetings of the AEA, New Orleans, LA.

Masters, W. A., Wiebe, K. D., 2000. Climate and agricultural productivity. Paper presented at the Conference on Biophysical Constraints in Tropical Agriculture, Harvard University.

McLeod, A. I., Li, W. K., 1983. Diagnostic checking ARMA time series models using squared-residual autocorrelations. *J. Time Ser. Anal.* 4, 269–273.

Mearns, L. O., Rosenzeig, C., Goldberg, R., 1997. Mean and variance change in climate scenarios: Methods, agricultural application, and measures of uncertainty. *Clim. Chang.* 35, 367–396.

Mendelsohn, R., Nordhaus, W., Shaw, D., 1994. The impact of global warming on agriculture: A Ricardian analysis. *Amer. Econ. Rev.* 84, 753–771.

MLMWR, 2010. Ministry of Land, Minerals and Water Resources Rainfall, Uganda Archive Data, 1993–2009.

Nalyongo, P. W., Emeetai-Areke, T. E., 1987. Groundnut and pigeonpea production and improvement in Uganda. Research on grain legumes in Eastern and Central Africa, Addis Ababa, Ethiopia. http://agropedia.iitk.ac.in/openaccess/sites/default/files/RA%2000116.pdf

NARO, 2010. Impact Assessment of the National Agricultural Research Organization (NARO). Final Report.

Naidu, R. A., Kimmins, F. M., Deom, C. M., Subramanyam, P., Chiyembekeza, A. J., Van der Merwe, P. J. A., 1999. Groundnut rosette: A virus disease affecting groundnut production in sub-Saharan Africa. *Plant Dis.* 83, 700–709.

Nkamleu, G. B., 2004. Productivity growth, technical progress and efficiency change in African agriculture. *Afr. Develop. Rev.* 16(1), 203–222.

Okello, D. K., Biruma, M., Deom, C. M., 2010. Overview of groundnut research in Uganda: Past, present and future. *Afr. J. Biotech*. 9, 6448–6459.

Orindi, V. A., Eriksen, S., 2005. Adaptation to climate change in the development process in Uganda. Research on African Centre for Technology Studies (ACTS), Kenya. http://www.acts.or.ke/dmdocuments/ecopolicy15.pdf

O'Connell, S. A., Ndulu B.J., 2000. Africa's growth experience: A focus on sources of growth. Paper presented at AERC Workshop on Explaining African Economic Growth, Nairobi, Kenya.

Phillips, J. G., Cane, M. A., Rosenzweig, C., 1998. ENSO, Seasonal rainfall patterns and simulated maize yield variability in Zimbabwe. *Agric. For. Meteor*. 90, 39–50.

Rajagopalan, B., Lall, U. Cane, M. A., 1997. Anomalous ENSO occurrences: An alternative view. *J. Clim.*, 10, 2351–2357.

Rao, C. R., 1970. Estimation of heteroskedastic variances in linear models. *J. Amer. Stat. Assoc.* 65, 161–172.

Rezek, J. P., Campbell, R. C., Rogers, K. E., 2011. Assessing total factor productivity growth in Sub-Saharan African agriculture. *J. Agric.. Econ*. 62(2), 357–374.

Rosenzweig, C., 1989. Global climate change: Predictions and observations. *Amer. J. Agric. Econ.* 71, 1265–1271.

Sandra M. N.M., 1998. Country Pasture/Forage Resource Profiles. Grassland and Pasture Crops. http://www.fao.org/ag/AGP/AGPC/doc/Counprof/uganda.htm

Schlenker, W., Lobell, D. B., 2010. Robust negative impacts of climate change on African agriculture. *Environ. Res. Lett.* 5, 1–8.

Sherlund, S. M., Barrett, C. B., Adesina, A. A., 2002. Smallholder technical efficiency controlling for environmental production conditions, *J. Dev. Econ.* 69/1, 85–101.

Smartt, J., 1994. The groundnut in farming systems and the rural economy: A global view, in J. Smartt, editor, The Groundnut Crop: A Scientific Basis for Improvement. Chapman & Hall, London, pp. 664–699.

Tesfaye, H., 1988. Causes and characters of drought in Ethiopia. *Ethiopian J. Agric. Sci*. 10, 85–97.

Trenberth, K. E., Hoar, T. J., 1996. The 1990–95 El Niño–Southern Oscillation event: Longest on record. *Geophys Res. Lett*. 23, 57–60.

Tsegay, W. G., 1998. El Niño and drought early warning in Ethiopia, in Using Science Against Famine: Food Security Early Warning System and El Niño, Internet Journal of African Studies.

Ubilava, D. El Niño, La Niña, and world coffee price dynamics, 2012. *Agric. Econ.* 43, 17–26.

UN (United Nations), 2008. The Millennium Development Goals Report: 2008. New York, NY.

Wang, G., 2005. Agricultural drought in a future climate: Results from 15 global climate models participating in the IPCC 4th assessment. *Clim. Dyn.* 25, 739–753.

Wangai, A. W., Pappu, S. S., Pappu, H. R., Deom, C. M., Naidu, R. A., 2001. Distribution and characteristics of groundnut rosette disease in Kenya. *Plant Dis.* 85, 470–474.

White, H., 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econom.* 48, 817–838.

Winter, P., Muragi, R., Sadoulet, E., de Janvry, A., 1996. Climate change, agriculture, and developing economies. Department of Agricultural and Resource Economics, Division of Agriculture and Resource Economics, University of California at Berkley, Working Paper No. 785.

World Bank, 2008. World Development Report 2008: Agriculture for Development.

Yang, S. R., Koo, W. W., Wilson, W. W., 1992. Heteroskedasticity in crop yield models. *J. Agric.Res Econ.* 17, 103–109.

Table 1. Definition of Variables

Variable	Unit	Definition	N*	Mean	Minimum	Maximum
Panel A: N=333						
Q	Ton	Groundnut production	333	3633.5	39.0	16764.0
L	Hectare	Land area	333	5240.2	83.0	19430.0
Y	Kilogram/ Hectare	Yield	333	682.0	340.0	1116.0
FS_i	Dummies	Farming systems (i=1, 2,…13)	333	N/A**	N/A	N/A
T	Number	Mean-corrected time trend is converted from (1,… 9) to (-4,…4)	333	N/A	N/A	N/A
TD	Dummy	1 if the observation is in the specific year	333	N/A	N/A	N/A
WP	Dummy	1 if the year is in the warm phase of ENSO	333	N/A	N/A	N/A
CP	Dummy	1 if the year is in cold phase of ENSO	333	N/A	N/A	N/A

Variable	Unit	Definition	N*	Mean	Minimum	Maximum
Panel B: N=195						
Q	Tons	Groundnut production	195	4671.5	168.0	16764.0
L	Hectares	Land area	195	6802.4	361.0	19430.0
Y	Kilogram/ Hectare	Yield	195	685.2	439.6	1116.0
R	Millimeters	11-month (February to December) average rainfall***	195	129.9	83.5	177.5
FS_i	Dummies	Farming systems (i=1, 2,…13)	195	N/A	N/A	N/A
T	Number	Mean-corrected time trend, i.e., converted from (2,… 9) to (-3,…4)	195	N/A	N/A	N/A
TD	Dummy	1 if the observation is in the specific year	195	N/A	N/A	N/A

Notes:
* N is the number of observations. Rainfall data are available for only 195 out of 333 observations.
** Mean, minimum, and maximum are not computed for dummy variables.
*** 11-month rainfall data: the average rainfall was calculated from February to December.
N/A: Not Available

Table 2. Farming Systems, Meteorological Stations, and Districts in Uganda

Farming System (FS)	Meteorology Station (MS)*		District		
	Name	MS Symbol**	Name	District Number***	MS Number
(FS1) Acholi Sub FS	Gulu	A	Gulu	17	A
(FS1) Acholi Sub FS	Gulu		Kitgum	42	A
(FS2) Ankole FS Agro Pastoral	Mbarara	B	Bushenyi	12	B
(FS2) Ankole FS Agro Pastoral	Mbarara		Mbarara	55	B
(FS3) AnkoleMontane	Kasese	C	Rukungiri	71	C
(FS4) Busoga	Jinja	D	Iganga	20	D
(FS4) Busoga	Jinja		Jinja	21	D
(FS4) Busoga	Jinja		Kamuli	30	D
(FS5) Karamoja FS	Soroti	E	Moroto	57	E
(FS6) Karamoja/Pastoral	Soroti		Kotido	44	E
(FS7) Lake Albert Crescent	Kasese	C	Kabarole	24	C
(FS7) Lake Albert Crescent	Kibale	F	Kibaale	37	F
(FS7) Lake Albert Crescent	Masindi	G	Hoima	18	G
(FS7) Lake Albert Crescent	Masindi		Masindi	52	G
(FS8) Lake Victoria Crescent	Entebbe	H	Kalangala	27	H
(FS8) Lake Victoria Crescent	Kampala	I	Kiboga	38	I
(FS8) Lake Victoria Crescent	Kampala		Luwero	48	I
(FS8) Lake Victoria Crescent	Kampala		Masaka	51	I
(FS8) Lake Victoria Crescent	Kampala		Mpigi	59	I
(FS8) Lake Victoria Crescent	Kampala		Mubende	60	I
(FS8) Lake Victoria Crescent	Kampala		Mukono	61	I
(FS8) Lake Victoria Crescent	Kampala		Rakai	70	I
(FS9) Lango Sub FS	Lira	J	Apac	5	J
(FS9) Lango Sub FS	Lira		Lira	47	J
(FS10) Montane	Kabale	K	Kabale	23	K
(FS10) Montane	Kasese	C	Kisoro	41	C
(FS10) Montane	Tororo	L	Kapchorwa	33	L
(FS10) Montane	Tororo		Mbale	54	L
(FS11) Montane/Lake Albert Crescent	Kasese	C	Bundibugyo	11	C
(FS11) Montane/Lake Albert Crescent	Kasese		Kasese	34	C
(FS12) Teso	Soroti	E	Pallisa	69	E
(FS12) Teso	Soroti		Soroti	74	E
(FS12) Teso	Soroti		Kumi	45	E
(FS12) Teso	Tororo	L	Tororo	75	L
(FS13) West Nile	Arua	M	Arua	6	M
(FS13) West Nile	Arua		Moyo	58	M
(FS13) West Nile	Arua		Nebbi	65	M

*MS stands for Meteorological Station.
**The letters denote the matching Meteorological Station (e.g., "A" represents the "Gulu" MS).
***District number (e.g., "17"denotes "Gulu" according to Wikipedia
http://en.wikipedia.org/wiki/Districts_of_Uganda)

Table 3. F-tests between Translog and Cobb–Douglas Models

OLS	Time Trend	Preferred Model	Time Dummies	Preferred Model
Base Model	26.9***	TL	120.3***	TL
Rainfall Model	11.5***	TL	26.83***	TL
ENSO Model	39.4***	TL	120.3***	TL

GARCH	Time Trend	Preferred Model	Time Dummies	Preferred Model
Base Model	62.1***	TL	145.1***	TL
Rainfall Model	20.6***	TL	3.22**	TL
ENSO Model	40.2***	TL	143.26***	TL

Note: ***indicate 1% significance levels and **indicate 5% significance level.

Table 4. Translog Output Models with Time Trend for Uganda Groundnut Production

Variables	GARCH Base Model (Model 1)		GARCH Rainfall, Time Trend (Model 2)		GARCH ENSO, Time Trend (Model 3)		OLS ENSO, Time Trend (Model 3-OLS)	
	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
Intercept	0.2158**	0.1010	0.1165	0.1839	0.1142***	0.0176	0.1235***	0.0194
lnL	0.9874***	0.0043	0.9576***	0.0077	0.9641***	0.0065	0.9611***	0.0064
lnR	N/A	N/A	0.0768	0.0557	N/A	N/A	N/A	N/A
T	-0.1381***	0.0196	-0.0449	0.0460	-0.0347***	0.0017	-0.0347***	0.0021
(1/2)lnL*lnL	-0.0282***	0.0024	-0.1039***	0.0119	-0.0559***	0.0057	-0.0564***	0.0056
(1/2)lnR*lnR	N/A	N/A	-0.0742	0.4238	N/A	N/A	N/A	N/A
$(1/2)T^{*}T$	-0.0573***	0.0095	-0.0003	0.0057	0.0060***	0.0013	0.0059***	0.0016
lnL*lnR	N/A	N/A	0.0072	0.0211	N/A	N/A	N/A	N/A
lnL*T	-0.0004	0.0005	0.0002	0.0016	0.0026**	0.0011	0.0027*	0.0012
lnR*T	N/A	N/A	-0.0016	0.0250	N/A	N/A	N/A	N/A
CP	N/A	N/A	N/A	N/A	0.0800***	0.0110	0.0801***	0.0129
WP	N/A	N/A	N/A	N/A	-0.3651***	0.0134	-0.3648***	0.0157
FS1	0.0600**	0.0295	0.2535***	0.0433	0.1278***	0.0247	0.1315***	0.0265
FS2	-0.2166**	0.0937	N/A	N/A	-0.0877***	0.0220	-0.1017***	0.0244
FS3	-0.2426***	0.0937	N/A	N/A	-0.1340***	0.0305	-0.1525***	0.0322
FS4	-0.1984**	0.0918	-0.1775	0.9421	-0.0779***	0.0199	-0.0854***	0.0211
FS5	-0.1758*	0.0911	-0.1619	0.8763	-0.1061***	0.0327	-0.1200***	0.0339
FS6	-0.1751*	0.0902	-0.2628	0.8711	-0.1349***	0.0308	-0.1424***	0.0317
FS7	-0.1388	0.0898	-0.2324	0.8380	-0.1139***	0.0187	-0.1190***	0.0210
FS8	-0.2415***	0.0903	-0.3470	0.2849	-0.1508***	0.0190	-0.1632***	0.0208
FS9	-0.1587*	0.0903	-0.1796	0.2717	-0.0136	0.0218	-0.0168	0.0242
FS10	-0.1695*	0.0904	-0.1468***	0.0000	-0.0520**	0.0212	-0.0631***	0.0229
FS11	-0.2065**	0.0939	N/A	N/A	-0.0649**	0.0265	-0.0881***	0.0287
FS12	-0.0355	0.0921	-0.1318**	0.525	0.1150***	0.0181	0.1080***	0.0201
Observations	333		195		333		333	
F-Test	N/A		0.82		523.89***		N/A	
R^2	0.9926		0.9907		0.9973		0.9972	

Note: In Table 4 and 5 ***, **, and * indicate 1%, 5%, and 10% significance levels. N/A=no data

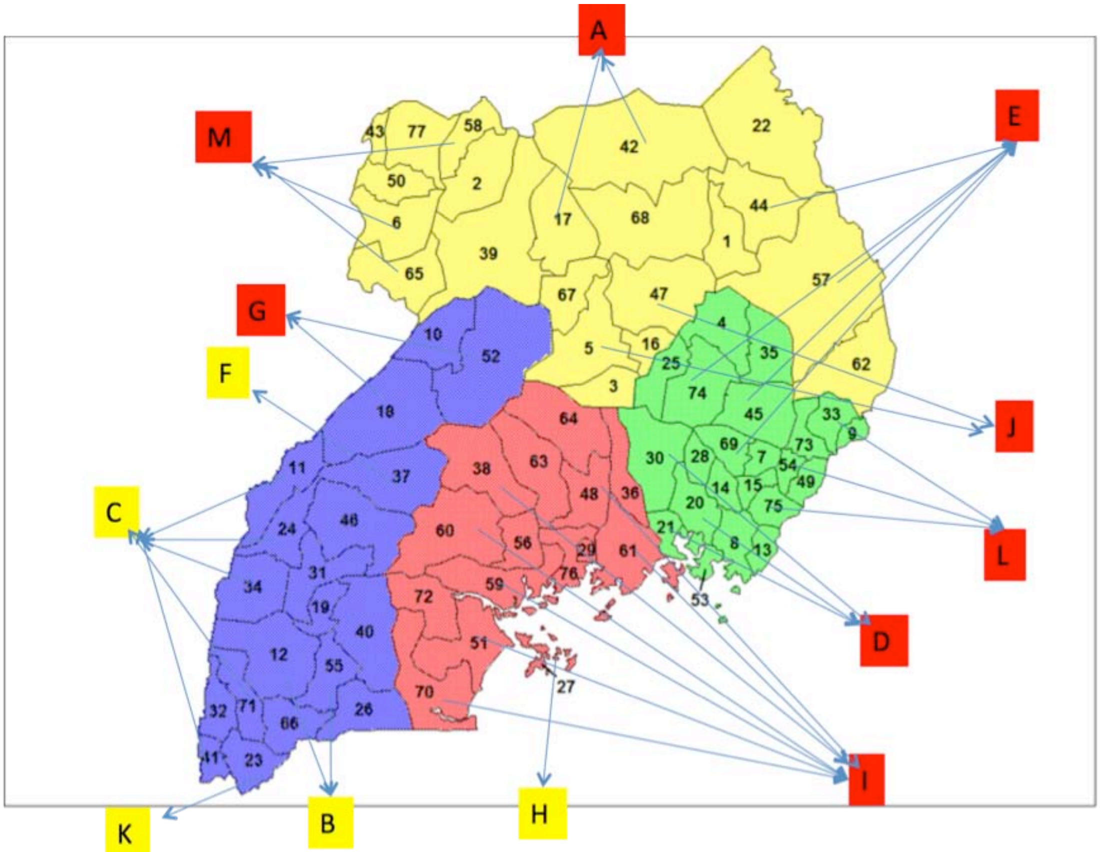
Table 5. Translog Output Models with Time Dummies for Uganda Groundnut Production

Variables	GARCH Base Model (Model 7)		GARCH Rainfall, Time Dummy (Model 8)		GARCH ENSO, Time Dummy (Model 9)		OLS ENSO, Time Dummy (Model 9 OLS)	
	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
Intercept	0.2529***	0.0136	0.3303***	0.0128	0.2529***	0.0136	0.2709**	0.0195
lnL	0.9698***	0.0053	0.9495***	0.0177	0.9689***	0.0053	0.9617***	0.0058
lnR	N/A	N/A	0.0046	0.0275	N/A	N/A	N/A	N/A
T	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
*(1/2)lnL*lnL*	-0.0546***	0.0045	-0.0570**	0.0185	-0.0546***	0.0045	-0.0557***	0.0051
*(1/2)lnR*lnR*	N/A	N/A	-0.0395	0.1879	N/A	N/A	N/A	N/A
$(1/2)T^{*}T$	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
*lnL*lnR*	N/A	N/A	0.0107	0.0253	N/A	N/A	N/A	N/A
*lnL*T*	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
*lnR*T*	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
CP	N/A	N/A	N/A	N/A	-0.1297***	0.0103	-0.1286***	0.0166
WP	N/A	N/A	N/A	N/A	-0.5460***	0.0103	-0.5449***	0.0166
FS1	0.1207***	0.0180	0.1088***	0.0185	0.1207***	0.0180	0.1302***	0.0240
FS2	-0.0739***	0.0156	N/A	N/A	-0.0739***	0.0156	-0.1011***	0.0221
FS3	-0.1160***	0.0227	N/A	N/A	-0.1160***	0.0227	-0.1513***	0.0292
FS4	-0.0696***	0.0142	-0.1037**	0.0446	-0.0696***	0.0142	-0.0851***	0.0200
FS5	-0.0897***	0.0253	-0.1295	0.1014	-0.0897***	0.0253	-0.1191***	0.0308
FS6	-0.1250****	0.0245	-0.1633	0.1162	-0.1250***	0.0245	-0.1414***	0.0287
FS7	-0.1078***	0.0129	-0.1324	0.1178	-0.1078***	0.0129	-0.1183***	0.0190
FS8	-0.1367***	0.0137	-0.1554***	0.0170	-0.1367***	0.0137	-0.1623***	0.0188
FS9	-0.0123	0.0151	-0.0043	0.0234	-0.0123	0.0151	-0.0172	0.0220
FS10	-0.0389**	0.0155	-0.0394	N/A	-0.0389**	0.0155	-0.0630***	0.0208
FS11	-0.0393**	0.0193	N/A	N/A	-0.0393**	0.0193	-0.0876***	0.0260
FS12	0.1200***	0.0125	0.1052***	0.0084	0.1200***	0.0125	0.1080***	0.0182
TD2	0.0242***	0.0103	N/A	N/A	0.0242***	0.0103	0.0249***	0.0166
TD3	-0.0610**	0.0103	-0.0899***	0.0107	-0.0610***	0.0103	-0.0602***	0.0166
TD4	-0.0621***	0.0103	-0.0905***	0.0107	-0.0621***	0.0103	-0.0612***	0.0166
TD5	-0.2187***	0.0103	-0.2451***	0.0106	-0.2187***	0.0103	-0.2177***	0.0166
TD6	-0.5460***	0.0103	-0.5713	0.0103	N/A	N/A	N/A	N/A
TD7	-0.1297***	0.0103	-0.1513***	0.0101	N/A	N/A	N/A	N/A
TD8	-0.1436***	0.0103	-0.1576***	0.0106	-0.0139	0.0103	-0.0140	0.0166
TD9	-0.2312***	0.0103	-0.2402***	0.0097	-0.2312***	0.0103	-0.2303***	0.0166
Observations	333		195		333		333	
F-Test	N/A		3.22**		1537.44***		N/A	
R^2	0.9982		0.9990		0.9982		0.9977	

Note: In Table 4 and 5 ***, **, and * indicate 1%, 5%, and 10% significance levels. N/A=no data

Figure 1. Map of Uganda

Figure 2. Map of Meteorology Stations and Districts in Uganda



Meteorology station	District
A	17,42
B	12,55
C	71,24,41,11,34
D	20,21,30
E	57,44,69,74,45
F	37
G	18,52
H	27
I	38,48,51,59,60,61,70
J	5,47
K	23
L	33,54,75
M	6,58,65

Note: Red designates the districts with rainfall data. Yellow designates the districts without rainfall data.