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Risk spillover between climate variables and the agricultural commodity market in East Africa

Jean-Luc Mubenga-Tshitaka, John W. Muteba Mwamba¹, Johane Dikgang and Dambala Gelo²

Abstract

This paper assesses the effect of extreme weather variability in predicting the impact on two agricultural crop-related variables: yield and production. We use a Markov-Switching time-varying copula to describe the joint dependence structure between extreme weather variability and crops in East Africa during the period 1961-2018. Understanding the risk associated with weather variability on agricultural production is crucial, as mitigation, and even adaptation, can then be made more effective. Climate data are divided into regimes: higher and lower regimes. The abnormal or higher regime is the period during which the temperature exceeds a certain threshold, while the lower regime is the period during which the rainfall is below a certain threshold. The findings show that there is strong dependence between weather variability and crops, meaning an increase in temperature or a decrease in rainfall is associated with a decrease in crop yield or production. The dependence is more significant when weather variability moves into either regime compared to the normal condition. The dependency in the higher regime tends to be more significant. This highlights the need to formulate policies that consider crop improvement strategies such as genetic crops, irrigation, and adaption under carbon dioxide (CO₂) fertiliser to mitigate the impact on food supply in the region.

Keywords: Dependence structure, weather variability, markov-switching, constant and time-varying copulas

JEL Code: Q1, Q2, Q10, Q54

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1. Introduction

Agriculture is one of the industries most affected by climate change, particularly extreme weather events (IPCC, 2012). In East Africa, for instance, agriculture is the most important sector, contributing up to 80 per cent of people's main income, and the livelihood of the population living in rural areas depends on it (Rapsomanikis, 2015). Such climate variability will have a devastating effect on agricultural products, as climate change induces food insecurity through extreme climate events (Xu et al., 2017).

Agriculture contributes up to 40 per cent to the Gross Domestic Product (GDP) in East Africa (Runge et al., 2004). This sector is dominated by traditional smallholder mixed farming of livestock, food crops, fishing and aquaculture, and is characterised by low inputs of physical capital, fertilisers and pesticides (Eriksen et al., 2008). The major crops produced in this region are maize, rice, potato, banana, cassava, beans, vegetables, sugar, wheat, sorghum, millet and pulses. Agriculture is mainly rain-fed agriculture (FAOSTAT, 2011), making this region highly dependent on climatic conditions (Slingo et al., 2009). In addition, agriculture is increasingly affected by extreme events such as drought, floods and rainstorms (Zegeye, 2018). These can increase the opportunity cost through years of foregone consumption.

The interaction between agriculture crops and climate anomalies is crucial for policy intervention. For instance, the agricultural insurance industry would want to understand whether or not to support farmers after experiencing losses due to weather extremes such as drought, or whether climate information can be considered to inform stakeholders about total revenue (Anderson et al., 2017). Insurance products can be used to transfer the risk of extreme weather events, to overcome the chronic problems of moral hazard, adverse selection, and other forms of asymmetric information that might affect the credit and insurance market. Still, for policymakers and farmers, water stress due to variability in rainfall might cause a delay in sowing, variability of the soil, or even change in crop management practices. In addition, due to people's dependence on agriculture in low-income countries, households cultivate their crops during only one growing season per year, with increasing variability in the periodic changes from drought and flooding. These might cause harmful effects on crop yields due to the rainfed nature of agriculture in the region.

This has pushed researchers to pay more attention to the dependency structure that exists between extreme weather events and agricultural outputs. An 'extreme weather event' refers to a hazardous weather condition that can provoke huge socio-economic losses (Funk, 2012; Lyon, 2014). Extreme weather events include excessive rainfall/floods (Hastenrath et al.,

2010), deficient rainfall, drought (Lott et al., 2013) and abnormally high temperatures (Mearns et al., 1984; Teixeira et al., 2013; Asseng et al., 2015).

The growing global interconnectedness and reciprocal interaction of economic and ecological systems may increase catastrophe susceptibility and risk. The global food system displays evidence of growing interconnectedness, as well as the potential for systemic risk. Due to the globalisation of the grain market, a food shortage or shock caused by drought in one or more major food-producing areas can result in a large increase in global food prices, putting food security at risk, especially in poorer nations (Gbegbelegbe et al., 2014). According to Von Braun (2008) and Mittal (2009), increased energy prices, shrinking world grain reserves, an increase in demand due to rising population and wealth, financial speculation in commodity markets, a decline in crop production due to decreased investment in agricultural research and development (R&D), and the use of grains for biofuel production are other factors that have contributed to the rapid rise in grain prices. Despite these factors, weather-related conditions in the agricultural sector are considered to be the major cause (Gaupp et al., 2017). Given that extreme weather events are projected to occur more frequently (IPCC, 2012), there is a need to better understand the implications of extreme weather events on agricultural output.

The copula technique is an important tool used to study the dependence structure between climate variables and crop yield/production. When evaluating the dependency structure, using a copula function has several advantages. First, copulas allow us to describe marginal behaviour and dependency structure separately. Second, we can use a copula function to determine the degree of dependence, as well as the structure of the dependence. Because a linear correlation does not provide information about the tail dependencies, a copula allows for asymmetric dependence (Naifar, 2011). Applications of copulas are also found in other domains, such as finance (D'Amico and Petroni, 2018; Huynh et al., 2020), hydrology (Ghosh, 2010; Madsen et al., 2014), meteorology and climatology (Lazaglou et al., 2019) and risk management (Luo and Shevchenko, 2009; Ghorbel and Trabelsi, 2014).

In the agricultural sector, several studies have applied copula methods to understanding yield loss due to climate variability. For instance, Vedenov (2008) employed the Gaussian copula to estimate the joint distribution of corn yields at farm and county levels. He found that co-movement between farm and county is observed in the lower tail of the distribution. Zhu et al. (2008) used the Gaussian and t-copula to capture the dependence structure between crop yield and prices, and found that there is dependence in the higher tail.

Increasingly, copula methods have also been used to construct the joint probability distribution between crop yield and drought (Li et al., 2015; Madadgar et al., 2017; Ribeiro et al., 2019;

Leng and Hall, 2019). For instance, Madadgar et al. (2017) employed copula techniques to examine the probability responses of crop yield variability to a change in drought conditions during the growing seasons in Australia. Recently, Nguyen-Huy et al. (2017) investigated the effect of multi-synoptic-scale climate drivers the El Niño-Southern Oscillation (ENSO) and the Inter-decadal Pacific Oscillation (IPO) Tripole Index (TPI) on Australia's wheat belt. Vine copulas were constructed to understand the joint behaviour of wheat yield and different climate variables. When the bivariate copula model was considered, the results revealed enough evidence to support upper tail dependence, while trivariate copula forecasting ability showed that the accuracy of the prediction improves during La Niña. Nguyen-Huy et al. (2018) used 12 large-scale climate drivers to investigate spatio-temporal influence on variability of wheat yield in five major states across Australia for the period 1983-2013. Vine copulas revealed that there is a statistically significant negative correlation between the Indian Ocean Dipole and anomalous wheat yields in the early stage of the crop.

However, we realise that studies analysing the joint behaviour of climate-extreme variables and crop-related variables (price, production and yield) are rare. The study of Alidoost et al. (2019) is the only work found; it analyses the joint behaviour of climate-extreme indices with three crop-related variables (price, production and yield). The researchers used the C-vine copula and five families of the copula: Gaussian, Student-t, Clayton, Gumbel and Frank. The results confirm that copulas are adequate to describe multivariate dependencies, and can quantify the effect of extreme events and the uncertainty surrounding them. Studies such as Cannarozza et al. (2006) emphasise that changes observed in the precipitation regime directly impact agriculture, hydrology and ecosystems. Coupled with the climate-change risk due to increased temperature, this affects rainfall and seasonal patterns. Higher temperatures can also lead to increased evaporation, which reduces the available water. In general these changes in precipitation or extreme-weather events are characterised by asymmetric behaviour (Enriken and Lordan, 2012); thus, methods that accommodate the asymmetric behaviour observed in climate variables are suitable. The Clayton and Gumbel asymmetric Archimedean copulas, which exhibit greater dependence in the negative and positive tail respectively (Naifar, 2011; Zhang and Vijay, 2007), are particularly suitable – contrary to the Elliptical copulas, which accommodate mostly the elliptical distributions that are multivariate normal and Student-t distributions.

This study has two objectives. First, to investigate the joint behaviour of crop yield and production and climate variability in East Africa. This area is highly dependent on agriculture and dominated by small-scale rain-fed production. This paper is one of the first to model the

relation between crop yield, production and climate variables by making use of the time-varying copula technique in East Africa. Afuecheta and Omar (2021) have been the only researchers to use copulas in Africa and East Africa to study the dependence structure of climate variability in temperature and precipitation with crops related variables (yield and production). The findings reveal that climatic factors and most of the crops variables (yield/production) show strong dependence. However, the researchers failed to account for a time-varying structure in their analysis. To remedy that, we propose the use of time-varying Archimedean copulas.

Second, this paper assesses the impact of the extreme-weather events on agricultural output in East Africa by using rainfall and temperature, similarly to Afuecheta and Omar (2021). Most studies on climate variability in East Africa focus on rainfall rather than temperature (Shongwe et al., 2011; Anyah and Qiu, 2012; Nicholson, 2014). Contrary to Alidoost et al. (2019) and Afuecheta and Omar (2021), we argue that not all climate variability observed is harmful to agricultural outputs, but only when such variability exceeds a certain threshold. To study this, we consider a regime in which climatic factors produce extreme-weather events. A drought, for instance, is a period of time during which an area or region receives less rain than usual. However, it is impossible to tell when a drought will start. A drought may go unnoticed for weeks, months or even years before it is identified as a drought. Droughts may also end just as gradually as they began. They may occur in almost every climatic zone, including both high- and low-rainfall locations, and are usually caused by a decrease in the quantity of precipitation received over a long period of time, such as a season or a year. But droughts are exacerbated by high temperatures, high winds, low relative humidity, and the timing and features of rainfall, such as the distribution of wet days during crop growth seasons, rain strength and duration, and rain commencement and termination (Mishra and Singh, 2010).

‘Evapotranspiration’ is understood as the total quantity of water returned to the atmosphere due to higher temperatures. The rate of evapotranspiration is affected by sunlight, humidity, temperature and wind. Soils can lose moisture and dry conditions can occur when evapotranspiration rates are high. However, in cold conditions and during overcast weather, evapotranspiration rates may be low enough to compensate for periods of below-normal precipitation, and drought may be mild or non-existent (Moreland, 1993). This means an increase in the temperature level can lead to soil losing moisture, and dry conditions. For that circumstance we consider a regime in which climatic factors (rainfall and temperature) produce extreme or abnormal weather events (such as drought) at times, and normal events otherwise. ‘Abnormal’ is used to describe a period during which the temperature exceeds a certain

threshold or the precipitation is below a certain threshold. There is a gap in the literature regarding such regimes.

Our results show that there is strong dependence between weather variability and crops. The dependence is more pronounced when weather variability moves into the abnormal regime compared to normal conditions, as high-temperature and water-stress episodes may cause significant crop-yield losses. Our findings also reveal that such dependence is persistent in all countries and across crop products.

The rest of the paper is organized as follows: section 2 presents the model specifications, while section 3 describes the data and variables. Section 4 presents the results, and the last section concludes this report.

2. Methodologies

2.1 Markov Switching Model

To capture the time-varying dependence structure using copulas, a two-step approach is used, as in Patton (2006) and Mudiangombe and Muteba Mwamba (2019). In order to remove the effect of autocorrelation and heteroscedasticity in the data, the generalised autoregressive conditional heteroskedasticity (GARCH) type is considered.

2.1.1 Glosten, Jaganathan and Runkle GARCH (1993)

The GJR-GARCH (1,1) model can be expressed as follows:

$$r_t = \mu + \varepsilon_t = \mu + \sigma_t \eta_t, \quad (1)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1}, \quad (2)$$

where I_j is the indication functions with this condition: $I_{t-1}=1$ if $\varepsilon_{j-1} < 0$ and $I_{t-1} = 0$ if $\varepsilon_{j-1} \geq 0$, $\alpha_0 > 0$, $\alpha_1 \geq 0$ and $\beta \geq 0$

to ensure a positive conditional variance σ_t^2 , $\alpha_1 + \beta < 1$

to ensure that unconditional variance $var(\varepsilon_t) = \alpha_0 / (\alpha_1 + \beta)$ is defined $\eta_t \sim i. i. d. N(0,1)$.

2.1.2 Markov Regime Switching GJR-GARCH (MS-GJR-GARCH)

As in Augustyniak et al. (2014), Bauwens et al. (2010) and Francq et al. (2001), the GJR-GARCH(1,1) model can specified as follows:

$$r_t = \mu_{S_t} + \sigma_t(S_{1:t}) \eta_t, \quad (3)$$

$$\sigma_t^2(S_{1:t}) = \alpha_{0S_t} + \alpha_{1S_t} \varepsilon_{t-1}^2(S_{t-1}) + \beta \sigma_{t-1}^2(S_{1:t-1}) + \gamma \varepsilon_{t-1}^2 I_{t-1}(S_{1:t-1}), \quad (4)$$

where $\eta_t \sim i.i.d. \mathbb{N}(0,1)$. For each point in time, the conditional variance is $\sigma_t = var(r_t | r_{1:t-1}, S_{1:t-1})$,

where $r_{1:t-1}$ and $S_{1:t-1}$ are vectors (r_1, \dots, r_{t-1}) and (S_1, \dots, S_t) respectively. S_t is an unobserved ergodic time-homogeneous Markov chain process with k -dimensional discrete state space (S_t is assumed to take the integer values from 1 to k). The $K \times K$ transition matrix of the Markov chain is defined by the transition probabilities $\{\Pr [S_t = j | S_{t-1} = i]\}_{i,j=1}^k$. The vector $\theta = (\{\alpha_{0,i}, \alpha_{1,i}, \beta_i, \gamma_i\}_{i=1}^k, \{p_{ij}\}_{i,j=1}^k)$ represents the parameters of the model.

2.2 Copula: definition and basic properties

We consider a copula model to estimate the possible responses of crop yield and production to extreme climate events. To achieve this, we model the dependence between extreme climate events and crop yield or production using a copula function proposed by Nelsen (2007). Copula functions can model dependency between variables that do not follow the same distributions, including even non-normal distributions; thus accommodating non-linearity or underlying probability distributions.

We define copula as the n -dimensional distribution that forms a copula function, C . This function is limited in the interval $[0,1]^n$ with conditions that might be satisfied as follows:

- A copula is an n -increasing function.
- The copula function has margins C_j , where $j = 1, 2, \dots, n$, $C_j(t) = t$ for each t in $[0,1]$.

A distribution F of dimension p , with the distribution marginal F_j , the function copula can be written as follows:

$$F(z_1, \dots, z_p) = c(F_1(z_1), \dots, F_p(z_p)) \quad (5)$$

where C represents the copula function that links the marginal distributions, $F_j(z_1, \dots, z_p)$, $F_1(z_1)$ and $F_p(z_p)$ are the joint distribution: the marginal distribution of the variable z_1 and the marginal distribution of the variable z_p respectively, with $j = 1, \dots, p$, when all marginal distributions are continuous. The copula function can be written as follows:

$$c(k_1, \dots, k_p) = F(F_1^{-1}(k_1), \dots, F_p^{-1}(k_p)) \quad (6)$$

Then $z = F_1^{-1}(k_1), \dots, F_p^{-1}(k_p)$, therefore the copula density will be as follows:

$$c(k_1, \dots, k_p) = \frac{f(F_1^{-1}(k_1), \dots, F_p^{-1}(k_p))}{\prod_{j=1}^p f_j F_j^{-1}(k_j)} \quad (7)$$

There are two families of copula the elliptical and the Archimedean copulas; but our study focuses on the Archimedean Clayton and Gumble copulas. The Clayton copula is an

asymmetric Archimedean copula that displays greater dependence in the negative tail than in the positive tail, while the Gumble copula exhibits greater dependence in the positive tail. This is crucial given the nature of climate variables, which tend to show asymmetric behaviour.

2.3 Dynamic Archimedean Copulas

Engle's (2002) theory was adjusted by Patton (2006) for modelling bivariate time-varying for Archimedean copulas, based on an ARMA procedure. As proposed by Patton (2006a), over a sample for the practical procedure of copula remains static; while in Kendall's tau, the transformed copula parameters vary in the process of the evolution equation, expressed as:

$$\delta_y = \Lambda(\varpi + \alpha_2 \delta_{y-1} + \alpha_1 \frac{1}{10} \sum_{j=1}^{10} |k_{1,y-j} - K_{2,y-1}|) \quad (8)$$

where Λ is the logistic transformation; and then $\Lambda(t) = (1 + e^{-t})^{-1}$ and is allowed to keep, at all times, the order of the parameters of the Clayton copula, $\delta_y \in [0,1]$ and (k_{1y}, k_{2y}) , as are the observations at time y . The dynamic process restricted to a bivariate application is applied by Patton (2006a) via the absolute difference term $|k_{1,y-j} - k_{2,y-j}|$ called forcing variables. When there is impeccable positive dependence, this absolute difference is close to zero and entrains the parameter α_1 to be negative.

3. Data description

Data points for this study were sourced from FAOSTAT (FAO, 2011) from 1961 to 2018. We collected annual data for yield and production for most cash crops in the three countries in East Africa (Kenya, Tanzania and Uganda). We collected data on the yield and production for 12 agricultural products: banana, cassava, coffee, maize, potato, rice, sorghum, soybeans, sugar, sweet potato, tea, and wheat – unlike Alidoost et al. (2019), who used only potato – as different products might respond differently to weather extremes. Rather we considered these agricultural products similarly to Adhikari et al. (2015), who reviewed the impact of climate change on 14 strategic crops in eight sub-Saharan Africa countries. Afuecheta and Omar (2021) is another study that considers more than one agricultural product.

However, according to Abraha-Kahsay and Hansen (2016), climate change variability in temperature and precipitation during a specific season is more harmful to agricultural output than the annual variations observed in precipitation and temperature. To capture the changes taking place in the crucial growing season, the temporal disagreement statistical technique was considered, for transforming low-frequency (annual) data to high-frequency (monthly) data. The other reason for expanding the sample size is to obtain reliable results that avoid sample

bias. The study considers the temporal disagreement method proposed by Denton (1971). To smooth the yield and production data, the logarithmic yield and production sequences are obtained similarly to Xiang-dong et al. (2019), by the following expression:

$$\Delta O_i = \ln (O_t / O_{t-1}) \quad (9)$$

where $t = 1, \dots, n$; O_t being the observation at time t and O_{t-1} being the corresponding logarithmic yield or production of the agricultural products. Table 1 presents the descriptive statistics for the 12 agricultural products considered in this study.

Table 1: Summary of descriptive statistics for yield and production of agricultural products

Kenya												
Yield	Banana	Cassava	Coffee	Maize	Potato	Rice	Sorghum	Soybean	Sugar C	S. Pot	Tea	Wheat
Mean	0.095	0.052	0.008	0.075	0.115	0.057	0.119	0.001	0.041	0.137	0.062	0.091
Std dev	0.099	0.054	0.007	0.117	0.108	0.113	0.103	0.028	0.124	0.135	0.082	0.149
Skewness	3.496	4.925	2.472	5.167	3.157	6.973	2.503	-2.656	7.394	4.09	3.727	5.682
Kurtosis	31.273	39.504	18.326	36.314	30.081	59.726	16.419	11.362	64.337	46.822	15.496	43.705
J. Berra	0.829	0.829	0.829	0.829	0.829	0.829	0.829	0.829	0.829	0.829	0.829	0.829
Production												
Mean	0.068	0.061	0.04	0.104	0.081	0.042	0.075	0.001	0.084	0.053	0.057	0.126
Std dev	0.107	0.054	0.027	0.128	0.064	0.041	0.056	0.049	0.18	0.05	0.082	0.265
Skewness	5.237	3.007	3.523	4.894	2.687	4.071	2.121	-2.751	6.052	3.034	4.103	7.378
Kurtosis	37.006	28.217	38.702	42.393	25.782	38.511	13.923	18.818	47.429	26.916	20.633	67.526
J. Berra	0.829	0.829	0.829	0.829	0.829	0.829	0.829	0.83	0.829	0.829	0.829	0.829
Tanzania												
Yield												
Mean	0.025	0.1	0.107	0.032	0.106	0.075	0.024	0.014	0.096	0.059	0.055	0.055
Std dev	0.018	0.098	0.271	0.105	0.093	0.215	0.076	0.028	0.286	0.194	0.128	0.153
Skewness	1.748	1.823	5.074	8.426	3.326	5.866	7.732	4.982	7.458	6.315	5.53	6.67
Kurtosis	12.158	7.114	30.907	79.292	23.307	40.56	67.763	31.798	64.04	44.707	38.551	52.298
J. Berra	0.829	0.829	0.829	0.829	0.829	0.829	0.829	0.829	0.829	0.829	0.829	0.829
Production												
Mean	0.018	0.044	0.072	0.021	0.051	0.107	0.068	0.055	0.057	0.044	0.091	0.019
Std dev	0.037	0.099	0.182	0.05	0.11	0.01	0.166	0.069	0.128	0.05	0.086	0.04
Skewness	7.023	5.485	4.984	5.905	5.798	2.806	5.231	2.702	4.592	3.321	3.753	4.935
Kurtosis	58.031	37.525	29.848	41.011	38.333	9.839	31.161	14.444	24.736	21.241	35.067	30.56
J. Berra	0.829	0.829	0.829	0.829	0.829	0.829	0.829	0.829	0.829	0.829	0.829	0.829
Uganda												
Yield												
Mean	0.001	0.001	0.001	0.001	0.001	0.001	0.001	-0.001	-0.01	0.001	0.001	-0.001
Std dev	0.032	0.041	0.052	0.033	0.031	0.032	0.057	0.067	0.79	0.059	0.019	0.08
Skewness	-2.851	-0.43	-1.769	-2.099	-3.681	-0.908	-0.124	-1.093	6.252	-0.023	-1.516	0.242
Kurtosis	20.373	12.26	21.888	12.648	23.04	10.684	4.929	16.09	152.788	8.778	7.592	7.475

J.Berra	0.829	0.829	0.829	0.829	0.829	0.829	0.829	0.829	0.829	0.829	0.829	0.829
Production												
Mean	0.001	0.001	0.006	-0.008	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.001
Std dev	0.017	0.062	0.042	0.218	0.031	0.02	0.062	0.022	0.023	0.029	0.03	0.053
Skewness	-6.454	-0.338	-1.049	-5.28	-3.681	-6.957	0.01	-5.139	-3.698	-0.793	-2.862	-1.833
Kurtosis	57.61	3.447	8.169	163.17	23.04	63.48	2.527	37.303	31.421	4.997	29.908	12.535
J. Berra	0.829	0.829	8.169	0.829	0.829	0.829	0.829	0.831	0.829	0.829	0.829	0.829

Note: S. Pot stands for sweet potato and sugar C. for sugar cane

The findings reveal that the yield and production of wheat have the highest standard deviation, while sugar cane and coffee record the highest standard deviation in Tanzania for yield and production respectively. Uganda records the highest standard deviation for sugar cane and maize for yield and production respectively. The skewness coefficient that measures the asymmetric behavior in the distribution is positive for Kenya and Tanzania for both yield and production, while Uganda has non-positive asymmetric distribution, indicating the presence of the longer left-hand tail distribution for both yield and production. Jarque-Bera coefficients for all countries confirm that the normality assumption is rejected, implying that the yield and production data are not normally distributed, and suggesting that assuming joint normality may produce misleading results. The findings also reveal that the highest mean is achieved by sweet potato (yield) and wheat (production) in Kenya, followed by coffee (yield) and rice (production) in Tanzania; while the lowest mean value is observed in Uganda. We considered the Climate Research Unit (CRU) to be the main source of climate data, as did Barrios et al. (2008) and Abraha-Kahsay and Hansen (2016). The monthly data for temperature and precipitation are calibrated into the GRJ-GARCH (1,1) specification to take into account time-varying variability, as well as the asymmetric behavior of these climate variables.

Table 2 displays the outputs for rainfall using the GJR-GARCH model. This is contrary to Tol (1996), who pioneered the use of ARCH and GARCH models to model the mean and conditional variance of temperature, which depends linearly on the conditional variances of previous temperatures and prediction errors.

We relax the symmetric assumption of the ARCH-GARCH (1,1) and use the model that accommodates the asymmetric and fat tail distributions. Others studies, such as Franses et al. (2001) also used quadratic GARCH to model temperature, while Romilly (2005) used the seasonal ARIMA-GARCH (1,1) to model temperature. For that, we consider the GRJ-GARCH (1,1); Panel B in Table below 2 presents the output of the GJR-GARCH (1,1). Log-likelihood, the Akaike Information Criterion (AIC), and Schwarz's BIC were computed to compare

models, and the findings are reported in Panel C. All the information criterion coefficients point in favour of the GJR-GARCH (1,1).

Table 2: ARMA-GJR-GARCH parameters

	Temperature						Precipitation					
	Kenya		Tanzania		Uganda		Kenya		Tanzania		Uganda	
Panel A:												
	Param	P-V	Param	P-V	Param	P-V	Param	P-V	Param	P-V	Param	P-V
constant	0.00	0.00	-0.01	0.00	0.00	0.49	0.49	0.00	0.44	0.16	0.20	0.00
AR(1)	0.11	0.00	0.15	0.00	0.71	0.00	0.81	0.00	0.50	0.00	0.83	0.00
MA(1)	0.20	0.00	0.24	0.00	-0.97	0.00	-0.84	0.00	-0.27	0.05	-0.89	0.00
Panel B												
α_0	-0.05	0.00	-0.12	0.00	-0.02	0.00	0.48	0.00	0.51	0.00	-0.07	0.11
β_1	0.19	0.00	0.31	0.00	0.00	1.00	0.21	0.08	0.20	0.61	-0.30	0.00
λ_1	0.99	0.00	0.98	0.00	1.00	0.00	0.78	0.00	0.22	0.40	0.74	0.00
λ_1^*	0.01	0.00	-0.03	0.00	0.03	0.00	-0.39	0.00	0.09	0.56	0.06	0.45
skew	0.79	0.00	0.95	0.00	1.10	0.00	3.76	0.00	5.04	0.00	2.18	0.00
shape	31.72	0.21	21.77	0.16	13.79	0.02	2.19	0.00	3.14	0.00	3.43	0.00
Panel C												
eGARCH												
LL	2751.61		2549.76		2899.98		-1760.6		-1649.85		-1297.5	
AIC	-3.98		-3.68		-4.19		2.56		2.40		1.89	
BIC	-3.95		-3.65		-4.15		2.60		2.44		1.93	
iGARCH												
LL	2752.64		2543.95		2902.08		-1791.1		-1690.32		-1324.8	
AIC	-3.98		-3.67		-4.19		2.60		2.46		1.93	
BIC	-3.96		-3.65		-4.17		2.63		2.48		1.96	
GJR-GARCH												
LL	2753.70		2583.80		2903.23		-1790.4		-1651.35		-1324.7	
AIC	-3.98		-3.73		-4.19		2.61		2.40		1.93	
BIC	-3.94		-3.69		-4.16		2.64		2.44		1.97	
sGARCH												
LL	2753.68		2545.55		2903.22		-1790.6		-1652.06		-1324.8	
AIC	-3.98		-3.67		-4.19		2.60		2.40		1.93	
BIC	-3.95		-3.64		-4.16		2.64		2.43		1.96	

Panel A: Mean equation parameters ARMA (p,q), Panel B: Variation equation parameters GJR-Garch, Panel C: Information Criteria for Garch model selection

In the context of climate change, we can imply that any disturbances, such as temperature change, create subsequent temperature disturbances that require time to settle down to reasonably normal conditions. As a result, certain summers may be considerably hotter and

longer than is typical, while other occurrences (such as rainfall shortages) may be stronger and last longer than usual. The uneven variance of heteroscedasticity of variables such as temperature and precipitation may take on an autoregressive structure, causing their conditional variance to be dependent on previous variances.

Coefficients of the conditional standard deviation are positive and significant for temperature, and negative and significant for precipitation. We are implying that an increase in temperature is associated with an increase in temperature volatility. This is also true for precipitation, where a change in rainfall pattern is associated with rainfall variability. Most of the conditional mean and variance coefficients are significant. The asymmetric coefficients are significant, confirming the presence of more variability in the tail of the distribution meaning more variabilities are observed in temperature in the high tail or higher regime, while such tendencies are observed in the lower regime for precipitation. More precipitation or less of the same magnitude, for instance, may have an unequal effect on the yield and production of crops in East Africa.

Table 3 below reports the estimates of the transition matrix for temperature and precipitation. It shows that neither of the two regimes is permanent, as all the parameters of the transition probability matrix are less than one.

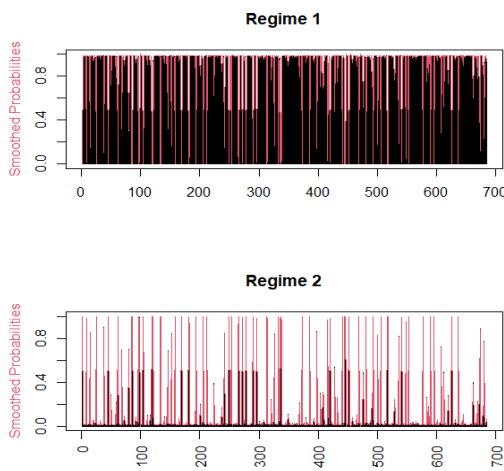
Table 3: Transition probability

Regime 1						
Temperature						
	Kenya		Tanzania		Uganda	
	Regime 1	Regime 2	Regime 1	Regime 2	Regime 1	Regime 2
Regime 1	0.7554	0.1608	0.7613	0.2389	0.6207	0.1190
Regime 2	0.2446	0.8392	0.2387	0.7611	0.3793	0.8810
Regime 2						
Precipitation						
	Kenya		Tanzania		Uganda	
	Regime 1	Regime 2	Regime 1	Regime 2	Regime 1	Regime 2
Regime 1	0.8752	0.1651	0.8520	0.2376	0.8677	0.1464
Regime 2	0.1248	0.8392	0.1480	0.7624	0.1323	0.8677

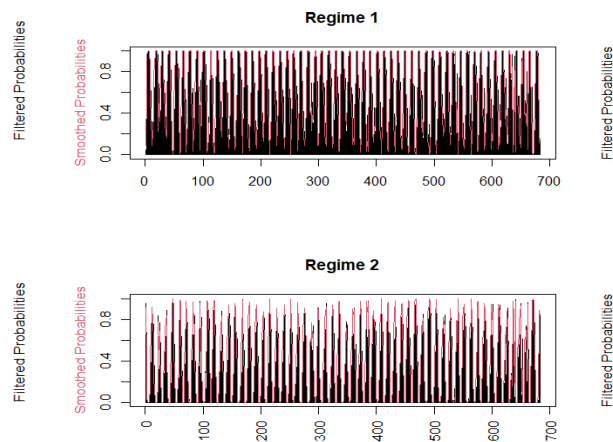
The estimated coefficients for Tanzania are the only coefficients that are almost equally likely to remain in either state or regime when there is variability in temperature. Other regime

systems for temperature and precipitation tend to remain in one state more than the other. For instance, precipitation variability has a higher likelihood of remaining in the second regime than in the first, while the opposite is observed for temperature. The probability of temperature switching from regime 1 (normal) to regime 2 (abnormal) is relatively stable; but once shifted into a regime, temperature tends to remain there for significant time. This causes soil to lose moisture, for instance, and the development of dry conditions in these countries. This implies that a higher probability infers that two regimes (either higher or lower) are highly persistent. Figure 1 below reinforces the presence of two regimes in the variability of temperature and precipitation.

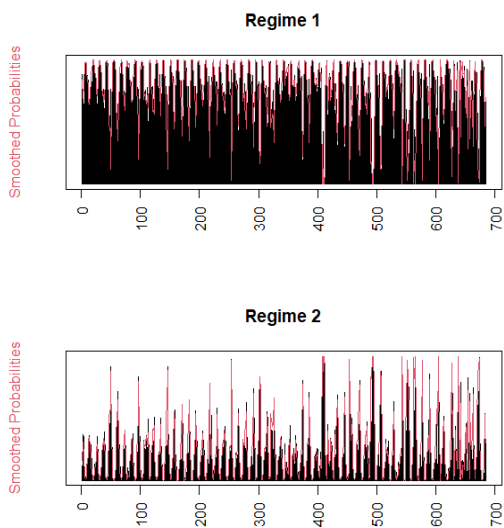
Kenya: Temperature



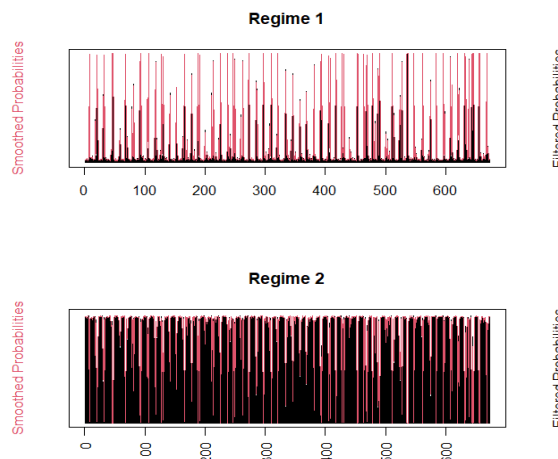
Tanzania: Temperature



Uganda: Temperature



Kenya: Precipitation



Tanzania: Precipitation

Uganda: Precipitation

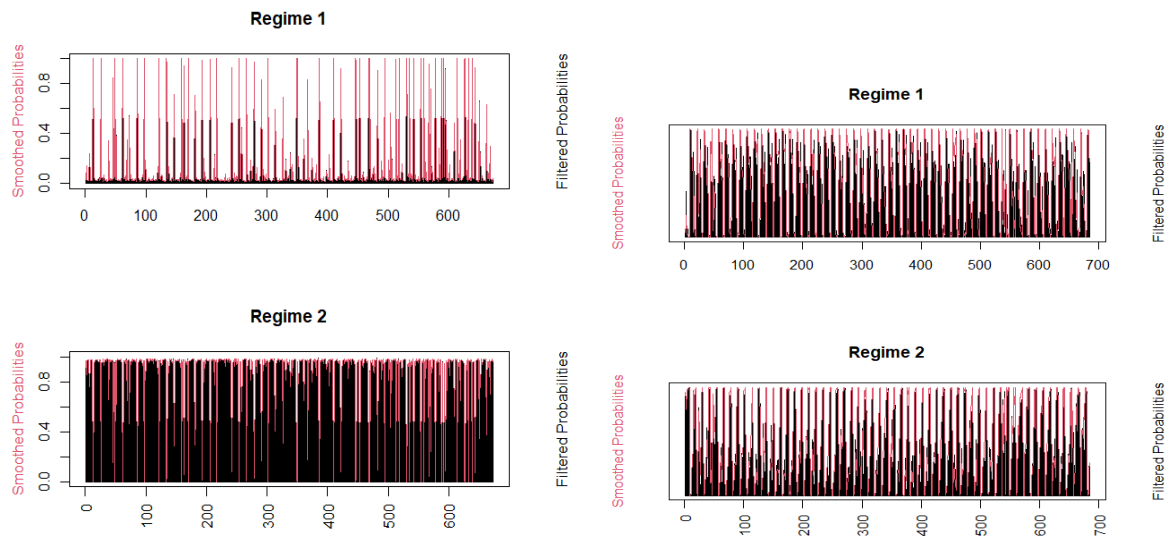


Figure 1: Transition probabilities plots for both regimes

Figure 1 also shows that there is more variability in temperature in the higher regime, while there is more variability in precipitation in the low regime. This is in line with the literature. For instance, Ongama and Chen (2017) emphasised that even though there was an increase in temperature in 1960, a sudden increase was also observed around 1994, with the highest warming rate of 0.05°C per year in 1990. Omondi et al. (2013) reported a significant reduction in total rainfall quantity and an increase in weather extremes in East Africa. The low part of Figure 1 also confirms the trend, with more variability, when precipitation variability passes into regime 2. Kenya and Tanzania show more variability in the lower regime than Uganda, while almost the same variability in temperature is observed in the higher regime in Tanzania.

4. Discussion of the results

This section empirically analyses the dependence structure between extreme weather variables and crop yield and production. Table 4 below reports the estimates of the pair yield and precipitation variability in the left tail dependence parameters of the time-varying Clayton copula in the lower regime. We notice that almost all parameters are significant, showing that the relationship influencing the extreme weather events is interconnected with the crop yield. The findings reveal that a larger parameter, $\bar{\omega}$, indicates a higher degree of dependency in the variability in yield of agricultural products and precipitation variability in the low regime. The results show large values, indicating a higher level of co-movement. The dependence

parameters are positive, implying that an increase in precipitation variation coincides with or accounts for the change in the yield crops, with a high likelihood of contagion effect among crops. For instance, the higher and most significant values are observed for products such as banana, maize, potato and wheat, while the lowest is recorded for products such as tea and wheat in Kenya.

Table 4: Estimated parameters of the time-varying Clayton copula in the lower regime for yield

		Kenya		Tanzania		Uganda	
	$\bar{\omega}$	0.9519	(0.3550)	0.3810	(0.2397)	0.2450	(0.1085)
Banana	α_1	-0.8658	(0.3673)	-1.0322	(0.3092)	-0.7676	(0.2284)
	α_2	2.2927	(0.8376)	0.9787	(0.4188)	-1.0214	(0.3429)
	$\bar{\omega}$	0.8558	(0.3761)	0.4241	(0.4213)	0.5352	(0.2189)
Cassava	α_1	-0.6259	(8.4018)	-0.6653	(0.4274)	-0.7329	(0.2270)
	α_2	-1.9164	(3.8527)	-1.4792	(1.1538)	-1.7216	(0.6003)
	$\bar{\omega}$	0.6206	(0.2033)	0.4359	(0.0929)	0.3673	(0.2873)
Coffee	α_1	-1.4294	(0.8143)	-0.8203	(0.1768)	-0.6926	(0.1711)
	α_2	-1.1558	(0.3721)	1.4913	(0.0319)	1.1032	(0.7580)
	$\bar{\omega}$	1.3137	(0.3493)	0.6118	(0.0018)	0.5284	(0.2116)
Maize	α_1	-0.6032	(0.2832)	-1.4534	(0.0232)	-0.2871	(0.1589)
	α_2	3.3020	(0.9659)	0.5482	(0.0023)	1.7410	(0.4643)
	$\bar{\omega}$	0.9224	(0.4534)	0.1061	(0.3273)	0.5059	(0.0075)
Potato	α_1	0.7238	(2.0323)	0.7462	(0.2108)	0.6878	(0.0102)
	α_2	-1.9062	(1.1114)	1.6508	(0.6347)	1.7447	(0.0020)
	$\bar{\omega}$	0.7462	(2.0604)	0.5061	(0.0018)	0.3206	(0.0053)
Rice	α_1	-1.4129	(0.5343)	-1.1918	(0.7847)	-0.5984	(0.0098)
	α_2	1.6505	(1.1742)	0.0223	(0.0172)	1.5461	(0.0048)
	$\bar{\omega}$	0.8007	(0.2373)	0.5638	(0.1541)	0.3598	(0.1922)
Sorghum	α_1	-0.4187	(0.7015)	-0.8239	(0.1801)	-0.8232	(0.2767)
	α_2	-1.6741	(0.6530)	1.7731	(0.2713)	1.1500	(0.4871)
	$\bar{\omega}$	0.2950	(0.0981)	0.6175	(0.5757)	0.1945	(0.0224)
Soybeans	α_1	-1.3622	(0.3292)	-0.1746	(0.2258)	-1.5817	(0.2199)
	α_2	-1.2554	(0.2758)	-1.7790	(1.3305)	-0.6911	(0.3472)
	$\bar{\omega}$	0.2677	(0.5378)	0.5527	(0.3169)	0.5963	(0.2849)

Sugar	α_1	-0.6667	(0.3268)	-0.6601	(0.1874)	-0.3160	(0.2002)
	α_2	1.0914	(1.1538)	1.7899	(0.7449)	2.1617	(0.7903)
	$\bar{\omega}$	0.8011	(0.4338)	0.0001	(0.0025)	0.2222	(0.1350)
S. potato	α_1	0.7834	(0.7338)	-1.1474	(0.1861)	-0.7922	(0.1840)
	α_2	-1.7145	(0.9905)	-0.0098	(0.0023)	-0.7537	(0.3721)
	$\bar{\omega}$	0.0962	(0.0023)	0.1827	(0.0478)	0.2242	(0.0280)
Tea	α_1	-1.0701	(0.0260)	-1.5844	(0.4593)	-1.5460	(0.1935)
	α_2	0.7335	(0.0079)	1.0279	(0.2368)	0.7659	(0.0105)
	$\bar{\omega}$	1.4254	(0.5257)	0.3035	(1.7747)	0.2861	(0.0085)
Wheat	α_1	-0.3828	(0.1466)	-1.0327	(2.6727)	-0.7027	(0.0210)
	α_2	-4.0125	(1.4375)	0.991	(4.2544)	1.1728	(0.0063)

Notes: estimated parameters of time-varying Clayton copula with the dependence parameters and their standard errors in parentheses.

Bananas grown in Kenya using both traditional and contemporary propagation methods. (refer to Kabunga et al. 2012). Because a banana plant produces only about 5 to 20 suckers throughout its lifespan, the traditional technique of propagating bananas via suckers is a relatively sluggish procedure that results in poor yield. Furthermore, using banana suckers as planting materials allows pests and illnesses to proliferate, which is a major disadvantage of this traditional technique of propagation, resulting in Kenya's low yields for most of the products. However, we can infer from our results that extreme weather events account for the reduction in crop yield. It can also be attributed to the inability to utilise clean seeds, fertilisers, fungicides and irrigation, all of which have been blamed for Kenya's low yields. According to Wang'ombe and Van Dijk (2013), the most effective method to increase potato yield in Kenya is to use clean seeds, followed by irrigation, fungicides and fertilisers. The adoption rate for using clean seeds is the lowest, with only 4.5 per cent of the responder sample utilising them. Irrigation adoption was similarly modest, at 23 per cent, although fungicides and fertilisers were widely used, at 92 per cent and 96 per cent respectively.

Still, according to the same article, the adoption of the four innovations more than doubled yields, although the total quantity remained less than half of the leading world producers' 40 tons per hectare for crop products such as soybeans that have low dependence on rainfall. For soybeans to resume normal growth, farmers need two to three inches of rain in the week following the important growth phase, under the drought stress scenario (Ellsworth, 2002).

Maize, sugar, cassava, rice and soybeans are products that show more dependence in Tanzania and Uganda, while tea and sweet potato show less dependence.

There is high risk of a contagion effect from extreme rainfall events. The degree of persistence tends to be higher in Kenya, compared to the coefficients in Tanzania and Uganda. The reason might be that Kenya is a more drought-prone area due to high seasonal and annual variability over time and space. Results are in line with Mpelasoka et al. (2018) and Nicholson et al. (2018). However, the variability in yield might also come from the price, capacity, and irrigation technique employed during drought periods to avoid crop loss, the machines used, and fertilisers. For instance, Quiroga et al. (2011) reported that irrigated crops do not show evidence of the significant impact of water stress on yield. It should be noted that the production of any crop can increase if irrigation is intensified, but this can also lead to an increase in the rate of environmental degradation (Kang et al., 2009).

We note that the negative adjustment coefficients captured by α_1 are significant, meaning a significant variation in dependence over time. The degree of persistence captured by α_2 is mostly positive and significant, meaning that the variation observed in the dependence parameters tends to persist over time. Figures 2 and 3 below report that crop yield and production variations are common when dry circumstances prevail, and the crop has shown significant fluctuation over the last several decades. Figure 2 shows plots of the yield and production of the dependence structure of agricultural products with rainfall during the lower regime for Kenya. The results confirm that the dependence structure between yield and precipitation variabilities under drought stress tends to be significant and persistent over time. Overall, precipitation variability during the lower regime may explain the agricultural yield variations.

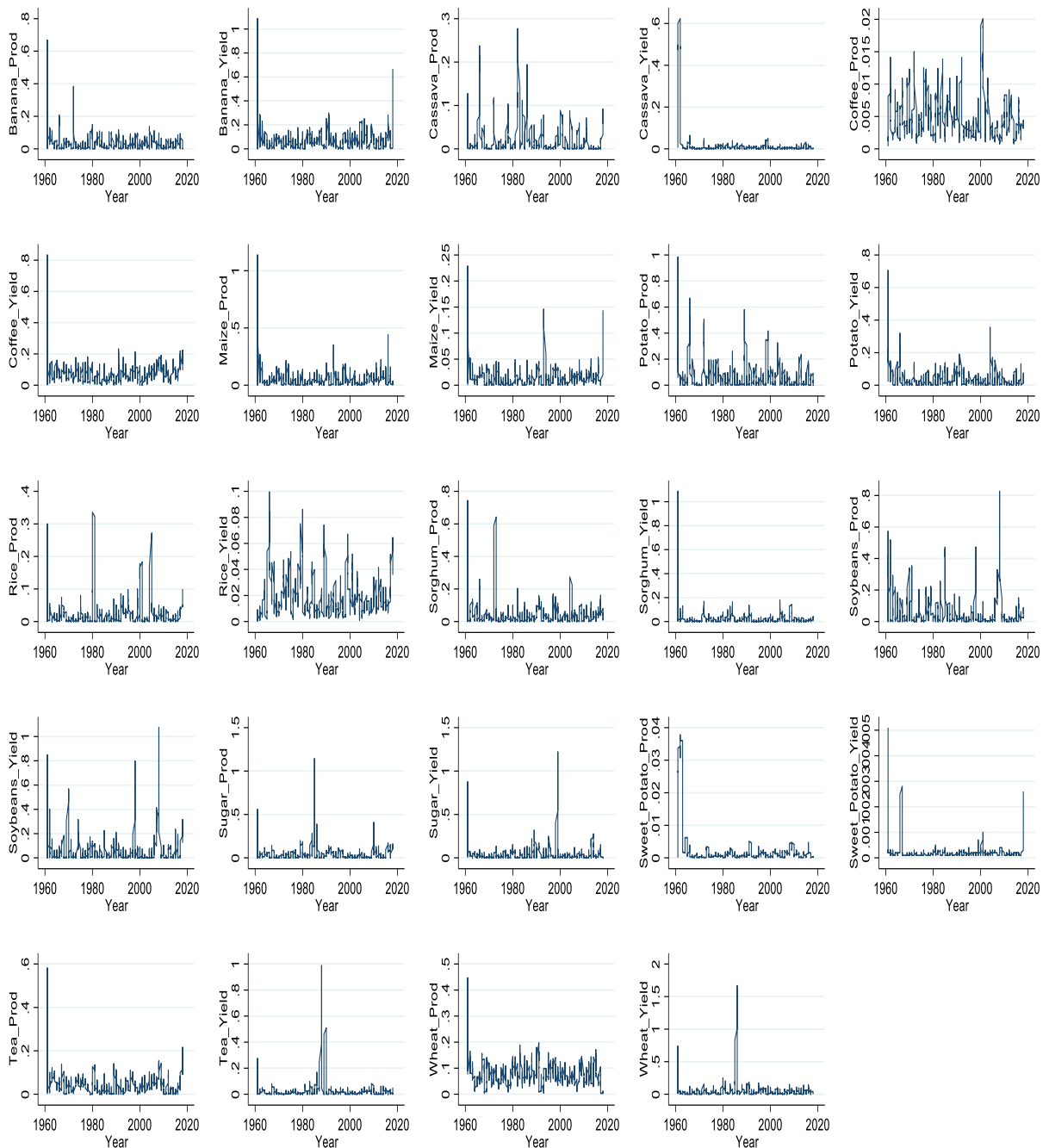


Figure 2: The conditional lower tail dependence of time-varying Clayton Copula in lower regime in Kenya

This relationship remains true for all crops; however, there are some differences in their strengths. Some products show less variability but are still very dependent over time, due mainly to the rain-fed nature of the agriculture sector in the region – in line with previous research, which found that precipitation has greater influence on rice and soybeans than on

wheat and maize (see Lobell and Field, 2007). There is also a greater influence on coffee and sweet potato. It is crucial to note that the extreme weather variability reported cannot explain a substantial percentage of yield or production variance, because there are numerous additional factors that influence variability; soil fertility, disease and pests, for example, may have a detrimental impact on crop output quantity and yield. This has been documented by a number of studies, including Feng et al. (2018).

For example, the region's total cereal output fell by almost 8% in 2019 because of lower harvests in countries such as Tanzania, Uganda and Kenya, due to extreme early season dryness, unpredictable weather, and insect assaults (FAO, 2020). Nonetheless, these findings suggest that the existence of a drought episode does not always predict a loss in production; but they do highlight the necessity for re-evaluating drought consequences by employing a probabilistic approach. Figure 3 below shows plots of the yield and production of the dependence structure of agricultural products and the temperature during the higher regime.

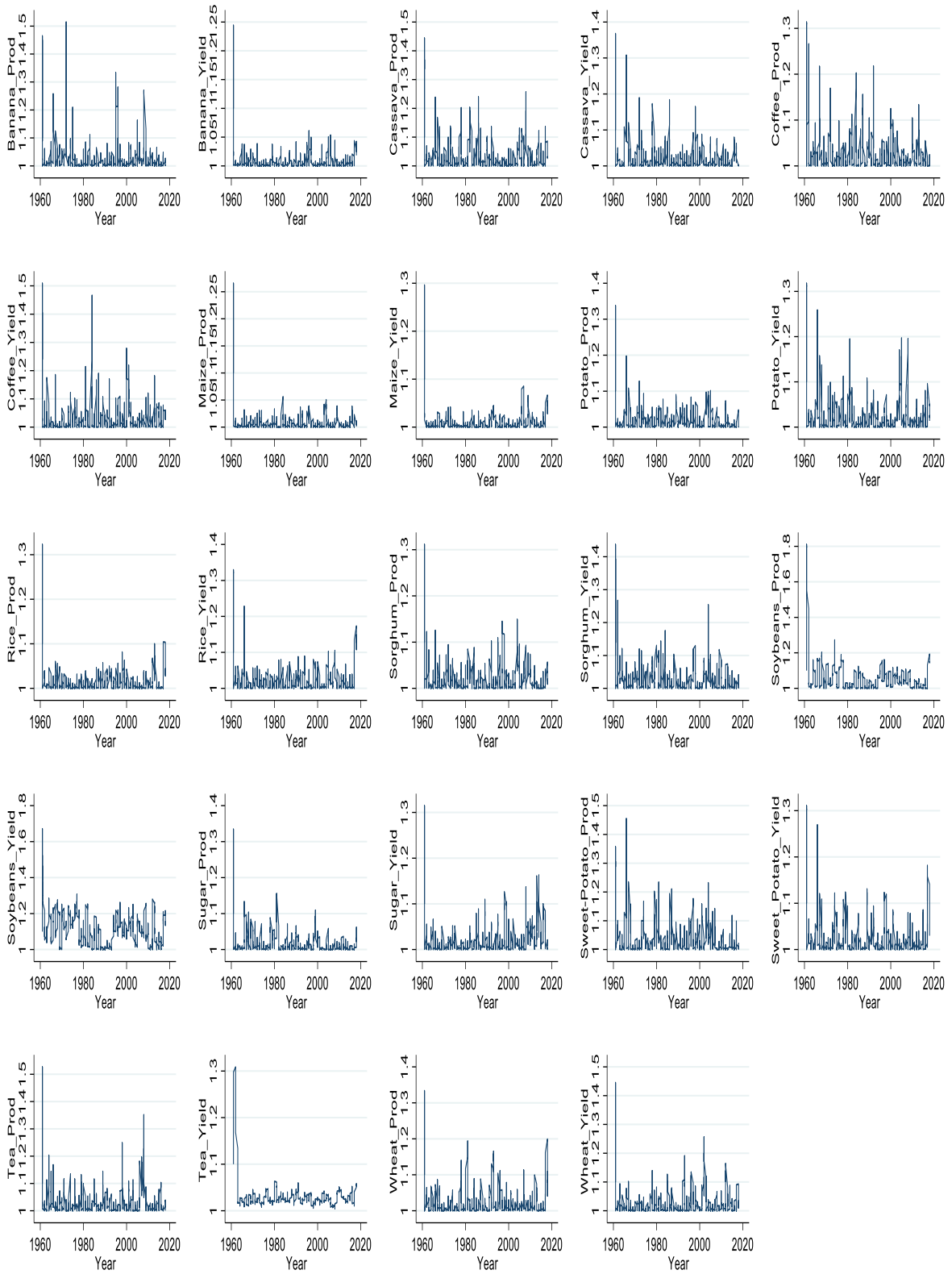


Figure 3: The conditional upper tail dependence of the time varying Gumbel copula in the higher regime.

The overall variation in the yield and temperature can be explained by the drought conditions observed when the temperature increases. Because of the increased temperature stress on the major grain crops, the projected air temperature rises for the rest of the twenty-first century imply that grain yields will continue to decline for the key crops (see Hatfield et al., 2011). The impact of the increase in temperature tends to be greater than the impact of the decrease in rainfall. Table 5 below shows the estimated time-varying Gumbel copula revealing the right tail dependency in the higher regime for yield and temperature variability.

Table 5: Estimated parameters of the time-varying Gumbel copula in the higher regime for yield

Country	Param	Kenya		Tanzania		Uganda	
Banana	$\bar{\omega}$	0.52570	(0.20830)	1.67190	(0.11630)	0.66210	(0.20800)
	α_1	-0.94470	(0.34750)	-0.77410	(0.10030)	-0.09310	(0.00830)
	α_2	1.19740	(0.45770)	1.44430	(0.19190)	1.12360	(0.13130)
Cassava	$\bar{\omega}$	1.43490	(0.62180)	1.64200	(0.14740)	1.42800	(0.13830)
	α_1	-0.46070	(0.07599)	-0.76350	(0.12990)	-0.44450	(0.10860)
	α_2	-2.39370	(0.53940)	1.61590	(0.21460)	-1.80270	(0.14670)
Coffee	$\bar{\omega}$	0.40970	(4.18600)	1.77680	(0.28100)	1.09570	(0.13320)
	α_1	-0.80880	(3.69210)	-1.00360	(0.26350)	-0.29400	(0.12600)
	α_2	1.09270	(1.22500)	1.39900	(0.17560)	-1.47810	(0.11580)
Maize	$\bar{\omega}$	1.16620	(0.84710)	1.68100	(0.13660)	1.39870	(0.11480)
	α_1	-0.40200	(0.77260)	-0.74250	(0.11670)	-0.52940	(0.10680)
	α_2	2.00420	(0.31670)	1.82260	(0.30420)	1.50570	(0.17470)
Potatoes	$\bar{\omega}$	1.43510	(1.08660)	1.78430	(0.09890)	2.20800	(0.14240)
	α_1	-0.74660	(0.95210)	-0.62180	(0.06180)	-1.48260	(0.18920)
	α_2	1.42490	(0.39800)	1.93240	(0.18980)	1.19150	(0.10690)
Rice	$\bar{\omega}$	0.74420	(0.52880)	1.00890	(0.00110)	1.42110	(0.14210)
	α_1	-1.08970	(0.38160)	-1.19010	(0.00130)	-0.49430	(0.11880)
	α_2	0.88290	(0.44300)	-0.06600	(0.00010)	-1.52340	(0.11690)
Sorghum	$\bar{\omega}$	2.63500	(0.10930)	1.55880	(0.30610)	1.13850	(0.13230)
	α_1	-1.78560	(0.25350)	-0.59640	(0.25900)	-0.46440	(0.13220)
	α_2	-2.01260	(0.33580)	-1.92860	(0.19960)	1.24380	(0.13160)
Soybeans	$\bar{\omega}$	1.43800	(0.26100)	1.75130	(0.08900)	1.47610	(0.12130)
	α_1	-1.66970	(0.21350)	-0.59150	(0.05320)	-0.54070	(0.09600)
	α_2	0.80480	(0.15090)	2.12450	(0.26890)	0.43680	(0.13250)
Sugar	$\bar{\omega}$	1.43800	(0.26100)	1.61730	(0.07050)	0.85870	(0.01370)
	α_1	-1.66970	(0.21350)	-0.73200	(0.08260)	-1.10400	(0.01770)

	α_2	0.80480	(0.15090)	1.54040	(0.13670)	0.54070	(0.09600)
	$\bar{\omega}$	0.73990	(0.58270)	1.71180	(0.16030)	1.08770	(0.13620)
S. potato	α_1	-1.10270	(0.42440)	-0.91500	(0.16280)	-0.32730	(0.12470)
	α_2	-1.02220	(0.45040)	1.20630	(0.19100)	1.33950	(0.11070)
	$\bar{\omega}$	1.85370	(0.18950)	1.62960	(0.13260)	1.36680	(0.17190)
Tea	α_1	-0.85120	(0.20660)	-0.65400	(0.11300)	-0.55030	(0.14710)
	α_2	2.58010	(0.41900)	-1.83270	(0.22250)	-1.49170	(0.14510)
	$\bar{\omega}$	1.78480	(0.31180)	1.73560	(0.13140)	1.46000	(0.08940)
Wheat	α_1	-0.91900	(0.30070)	-0.78610	(0.11480)	-0.51450	(0.07360)
	α_2	-2.06160	(0.25080)	1.76410	(0.17490)	1.75000	(0.15390)

Notes: estimate parameters of time-varying Gumbel copula with the dependence parameters and their standard errors in parentheses

In the higher regime, $\bar{\omega}$ parameters are also mostly positive and significant, expressing the pair dependence co-moves for these agriculture products and the temperature variation. However, the magnitude of the coefficient of dependence increases for most of the products, meaning an increase in temperature harms agricultural products. This is in line with Hulme et al. (2001), who forecast a significant rise in mean temperature and precipitation, as well as a significant increase in weather variability. This increase in the temperature has the potential to have a significant impact on agricultural production reduction and on livelihoods throughout the region (see Jagtap and Chan, 2000). According to Zhao et al. (2017), every degree Celsius increase in world mean temperature will lower global wheat yields by 6.0 per cent, rice yields by 3.2 per cent, maize yields by 7.4 per cent and soybean yields by 3.1 per cent without CO₂ fertilisation, successful adaptation and genetic improvement. As there are also some positive effects, the results are very diverse between crops and geographical locations.

Such high dependency on agricultural products to weather extreme events is detrimental, as high temperature increases water stress. Hence there is an urgent need to put mitigation strategies in place to reduce fuel emissions to cap global warming at 1.5°C (see IPCC, 2018). In addition, mitigation strategies tend to be more expensive for most developing countries as they do not have the appropriate technologies. Developing a cropping system in East Africa that is more resilient to hotter growing seasons and more extreme temperature events seems to be an inevitable necessity. This would reduce losses in yield and production for many crops across this region. Results are in line with Lobell *et al.* (2011), who noted that most key crops such as maize and wheat have recorded yield losses due to high growing-season temperatures. The adjustment and the degree of the persistence parameters are found to be significant during

the higher regime. The repeat impact of higher temperature can have an effect on soil quality and soil moisture, since temperature and quantity of water are vital physical elements for crop growth. Insufficient water and inadequate temperature conditions can hinder crop growth, particularly at the early phases of development, such as during seed germination (see Helms et al., 1996).

For instance, for each increase of 1°C in temperature, the yield of products such as mustard, wheat, soybean, groundnut and potato will decrease by three to seven per cent (Agrawal, 2009). This is because seed yields are very sensitive to brief episodes of hot temperature, particularly when these episodes coincide with the stage of crop development. The effect of temperature variability impact tends to be persistent in all countries and across products, as almost all the coefficients (α_2) are significant. The magnitude coefficients of dependence variation and persistence tend to increase over time and across all the countries.

5. Movement of tail dependence in the lower regime for variability

Annexure 2 reports the tail dependence of the time-varying Clayton copula in the lower regime on variability in yield and production of agricultural products. Annexure 2 presents the evolution of the lower tail dependence, with more fluctuations of the pair agricultural products. Remarkable fluctuation is seen for almost the period under investigation, confirming that the presence of continual extreme weather events such as drought impacts crops. Lyon (2014) noted that events such as drought have occurred more often in the East Africa region. In this case, the lack of water leads to inadequate water supply for crops and animals. Drought has a devastating effect on life and livelihoods in general, which might lead to food insecurity, malnutrition, epidemics, and human migration. This is in line with Ribeiro et al. (2019), who reported that in general, yield anomalies and drought conditions are related. Droughts and other extreme weather occurrences pose a significant threat to agricultural systems, particularly in rain-fed areas, and are important sources of risk for agricultural systems (Ben-Ari et al., 2016; Hernandez et al., 2017).

Policymakers should implement measures that tend to reduce the likelihood of the agricultural system continuing to rely on rainfall only. Irrigation enhances economic returns in developing countries, and can boost agricultural output by up to 400 percent (Khan et al., 2006). However, irrigation might have undesirable environmental impacts. About one-third of the irrigated areas in the globe have decreased production, driven by poorly managed water systems (FAO, 1998). For instance, approximately 50% of Asia's total freshwater resources are taken up by rice

cultivation (Barker et al., 2001). Approaches adopted to resolve environmental concerns should keep to the economically viable and the environmentally sustainable.

6. Movement of tail dependence in the higher regime of volatility

Annexure 2 also reports the tail dependence in the higher regime of yield and production for the three countries considered in this study. The figure shows that the movement of the upper tail dependence parameters of agricultural products and temperature shows more fluctuations when the temperature exceeds a certain threshold. This implies that more harm is caused when the variability exceeds a certain level, because of interconnectivity. Studies such as Hatfield and Prueger (2015) recognised that the major impact of an increase in temperature is observed during the reproductive phase. The study also recognised that maize yield is reduced by as much as 80 to 90% when the temperature moves above the normal temperature regime. Hatfield et al. (2011) added that crop productivity is reduced by 5% if the temperature increases by less than 1°C but can reach up to 50% reduction. Pettigrew (2008), Schlenker and Robert (2009) and Lobell and Field (2007) also concluded in their findings that reduction in crop yield is associated with increase in temperature. We also concluded that when the variability exceeds a certain threshold, and that increase is persistent for some time, the variation in yield and temperature due to dry conditions will be more significant.

7. Conclusion

In the East Africa region, agriculture is characterised by a small-scale farming system that relies on rain-fed and traditional practices. This paper intended to examine the dependence structure between weather variability and the crop-related variables yield and production, after the variability has exceeded a certain threshold. To achieve this, the paper employed a Markov-ARMA-GARCH time-varying copula to describe the joint dependence structure between extreme weather variability and crops in East Africa during the period 1961-2018. We collected data for 12 crops from FAOSAT, and weather-related variables from the Climate Research Unit (CRU). To obtain the threshold beyond or below which any variability in weather-related variables cause a harmful impact on crop yield or production, the Markov switching process was considered. Two families of Archimedean copula were used: a Clayton copula to capture the low regime, while a Gumbel copula describes the dependence in the higher regime. Copula techniques offer more flexibility in describing even complex and non-linear dependencies. Projections of crop productivity reduction under a scenario of climate change is 5% with temperature increases of less than 1°C (refer to Hatfield et al., 2011).

The results reveal a significant dependence pair structure in both regimes, implying the co-movement in the pair of the variations in agricultural products and weather extremes. This implies that there is a spillover risk. There is a presence of higher dependence among crop yields and production variations with the change in the climate variables. The coefficients indicating the degree of dependency in extreme weather variables and the crop-related variables show a higher level of co-movement, but there is more sensibility in the higher regime. We find evidence of dependency over time, as well as the contagion effect of the crop-related variables. The effects of the weather's extreme variability tend to be transmitted to other agricultural products.

As climate change will make current crops unsuitable for use in the future, a transition to heat-tolerant and drought-resistant crops will be required to ensure food security. Crop output is limited by crop type and planting area, soil degradation, growing environment, and water availability throughout the growing season. Water availability and agricultural output will decline in the future as temperatures rise and precipitation varies.

The results of this study show the benefits of the time-varying copula approach in dealing with climate variables as a lower and higher tail so the variability caused by climate-related variables can be accounted for. That is, if the marginal temperature and rainfall are not normally distributed (as is the case in this study), the multivariate model used is more likely to downplay the risk faced by the agricultural sector, as in this case it is a rain-fed one. The time-varying copula is built with the capacity to provide information about the degree or magnitude of crop dependency on climate variables if the dependency varies over time and the effect is persistent. Such inputs are crucial for policymakers in the agricultural sector. They can design policies based on the sensitivity and severity of the effect of weather variables on crops. Crops that are more resistant, such as sweet potato, should receive less attention compared to cereals such as maize or rice. Total agricultural output will improve if irrigated regions are extended; technology intended to reduce water waste, genetically-modified crops, irrigation, and adaptation under carbon dioxide (CO₂) fertiliser must be used to mitigate the impact on food supply in the region.

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Annexure 1: Estimated parameters of time-varying Clayton and Gumbel copula for production

Table A1: Estimate parameters of the time-varying Clayton copula in the lower regime for production

		Kenya		Tanzania		Uganda	
	$\bar{\omega}$	1.1352	(0.3358)	0.4353	(0.5311)	0.3573	(0.2876)
Banana	α_1	-0.5586	(0.2510)	-1.3376	(0.9685)	-0.8354	(0.2526)
	α_2	-2.6662	(0.7550)	-0.8385	(0.9967)	1.1958	(0.6465)
	$\bar{\omega}$	0.7727	(0.4189)	0.8551	(0.1923)	0.3616	(0.2757)
Cassava	α_1	-1.1043	(0.9209)	-0.0387	(0.0619)	-1.0229	(0.8080)
	α_2	-1.6341	(0.9817)	-1.9202	(0.4429)	1.1538	(0.7729)
	$\bar{\omega}$	0.2784	(2.7902)	0.4083	(0.0431)	0.2608	(0.0105)
Coffee	α_1	-1.5132	(6.5837)	-0.6304	(0.0678)	-1.3157	(0.0535)
	α_2	-0.5558	(5.6131)	1.6094	(0.0108)	-0.8429	(0.0024)
	$\bar{\omega}$	1.1461	(0.3936)	0.5577	(0.4683)	0.6685	(0.2201)
Maize	α_1	-0.6708	(0.3132)	-0.6131	(0.2825)	-0.5893	(0.1396)
	α_2	-2.9882	(0.9809)	1.9559	(1.1529)	2.1868	(0.5918)
	$\bar{\omega}$	1.2067	(0.2622)	0.9961	(0.2219)	0.5059	(0.0075)
Potato	α_1	-0.5952	(0.4155)	-1.1762	(0.2672)	-0.6878	(0.0102)
	α_2	-2.7488	(0.6011)	-2.0914	(0.4602)	1.7447	(0.0020)
	$\bar{\omega}$	0.9960	(0.4494)	0.4284	(0.0034)	0.3897	(0.2021)
Rice	α_1	-0.7257	(0.5343)	-0.7775	(0.0060)	-0.8737	(0.2257)
	α_2	-2.6471	(1.1299)	1.4960	(0.0009)	1.1494	(0.4387)
	$\bar{\omega}$	1.1038	(0.2031)	0.3494	(0.1831)	0.3836	(0.1727)
Sorghum	α_1	-0.3875	(0.1656)	-0.8453	(0.2475)	-0.8640	(0.2488)
	α_2	-2.5294	(0.4563)	1.1019	(0.4327)	1.1934	(0.4155)
	$\bar{\omega}$	0.3382	(0.0015)	0.0799	(0.0397)	0.3197	(0.0046)
Soybeans	α_1	-1.2491	(0.0091)	-1.0684	(0.5986)	-0.5907	(0.0087)
	α_2	1.2176	(0.0094)	0.4809	(0.2607)	1.3755	(0.0042)
	$\bar{\omega}$	0.4647	(0.2854)	0.7033	(0.0565)	0.5522	(0.2036)
Sugar	α_1	-1.0930	(0.5487)	-0.6403	(0.0520)	-0.6457	(0.1220)
	α_2	1.2971	(0.7374)	2.2295	(0.0335)	1.8809	(0.5054)
	$\bar{\omega}$	1.4013	(0.4093)	0.3978	(0.0575)	0.4500	(0.2539)
S. potato	α_1	-0.5577	(0.2143)	-0.6990	(0.1022)	-0.5537	(0.1495)
	α_2	-3.2187	(0.9690)	1.3053	(0.0008)	1.4225	(0.5730)
	$\bar{\omega}$	0.0399	(0.0004)	0.5683	(0.2754)	0.4315	(0.2554)
Tea	α_1	-1.1133	(0.0114)	-0.6607	(0.1393)	-0.9697	(0.5933)
	α_2	0.5867	(0.0043)	1.8007	(0.5884)	1.5674	(0.7996)
	$\bar{\omega}$	1.2667	(0.5610)	0.4929	(0.0198)	0.3388	(0.2530)
Wheat	α_1	-0.5592	(0.2940)	-0.8768	(0.0353)	-1.0511	(0.2386)
	α_2	-3.3273	(1.5121)	1.5277	(0.0119)	1.0043	(0.4802)

Notes: estimates parameters of time-varying Clayton copula with the dependence parameters and their standard errors in parentheses

Table A2: Estimates parameters of the time-varying Gumbel copula in the higher regime for production

		Kenya		Tanzania		Uganda	
Banana	$\bar{\omega}$	1.0338	(0.4407)	1.7011	(0.1245)	1.0460	(0.1293)
	α_1	-0.3472	(0.0870)	-0.7324	(0.0991)	-0.2628	(0.1145)
	α_2	1.5637	(0.3142)	-1.5567	(0.1591)	-1.4445	(0.1420)
Cassava	$\bar{\omega}$	0.4405	(0.0419)	1.672	(0.1394)	1.4280	(0.1383)
	α_1	-0.8753	(0.3514)	-0.6059	(0.0952)	-0.4445	(0.1086)
	α_2	-1.2371	(0.5569)	-2.1389	(0.2745)	1.8027	(0.1467)
Coffee	$\bar{\omega}$	0.8974	(0.0142)	1.6927	(0.1297)	0.7798	(0.1444)
	α_1	-1.1916	(0.0069)	-0.7077	(0.1136)	-0.0598	(0.0368)
	α_2	0.8746	(0.1046)	1.7525	(0.1864)	1.3975	(0.1571)
Maize	$\bar{\omega}$	1.3591	(0.2224)	1.1344	(0.0529)	1.3987	(0.1148)
	α_1	-0.4275	(0.1948)	-1.2906	(0.0528)	-0.5294	(0.1068)
	α_2	-2.5429	(0.3175)	-0.0809	(0.0158)	1.5057	(0.1747)
Potatoes	$\bar{\omega}$	1.7601	(0.3234)	1.7274	(0.0804)	0.9175	(0.0208)
	α_1	-0.7781	(0.3094)	-0.8590	(0.0829)	-1.1732	(0.0105)
	α_2	2.2078	(0.3379)	-2.1825	(0.2263)	-0.3845	(0.1308)
Rice	$\bar{\omega}$	1.6597	(0.2192)	1.7400	(0.1180)	1.4306	(0.1013)
	α_1	-0.7831	(0.2143)	-0.7007	(0.0839)	0.4399	(0.0836)
	α_2	1.8916	(0.2052)	-1.7440	(0.2480)	1.6088	(0.1250)
Sorghum	$\bar{\omega}$	1.2243	(0.0047)	2.1533	(0.0801)	1.3013	(0.1152)
	α_1	-1.4501	(0.0028)	-1.3634	(0.1327)	-0.4768	(0.1090)
	α_2	-0.4230	(0.0153)	1.5226	(0.1124)	-1.4558	(0.1294)
Soybeans	$\bar{\omega}$	1.8207	(0.2552)	1.0256	(0.0541)	1.4761	(0.1213)
	α_1	-0.9456	(0.2228)	-1.1987	(0.0529)	-0.5407	(0.0960)
	α_2	1.3632	(0.1526)	-0.0799	(0.0168)	0.4368	(0.1325)
Sugar	$\bar{\omega}$	1.4380	(0.2610)	1.1066	(0.0518)	0.8587	(0.0137)
	α_1	-1.6697	(0.2135)	-1.2737	(0.0529)	-1.104	(0.0177)
	α_2	0.8048	(0.1509)	-0.0658	(0.0195)	0.0827	(0.1265)
S. potato	$\bar{\omega}$	1.2614	(0.6669)	1.7180	(0.1244)	2.2281	(0.2099)
	α_1	-0.4966	(0.6515)	-0.8790	(0.1200)	-1.5720	(0.2400)
	α_2	-1.7521	(0.2452)	1.3149	(0.1582)	1.6625	(0.1460)
Tea	$\bar{\omega}$	1.9489	(0.1238)	0.9762	(0.0463)	1.5501	(0.1068)
	α_1	-0.8514	(0.1383)	-1.1553	(0.0631)	-0.4862	(0.0771)
	α_2	-2.6365	(0.3475)	-0.0848	(0.0991)	1.8627	(0.1788)
Wheat	$\bar{\omega}$	1.1234	(0.5083)	1.6654	(0.1219)	1.1569	(0.1090)
	α_1	-0.4105	(0.0828)	-0.7375	(0.1090)	-0.3966	(0.1049)
	α_2	1.7357	(0.2478)	-1.6342	(0.1729)	-1.2671	(0.0982)

Annexure 2: Reports the conditional lower and upper tail dependence of time varying Clayton and Gumble copulas for both regimes

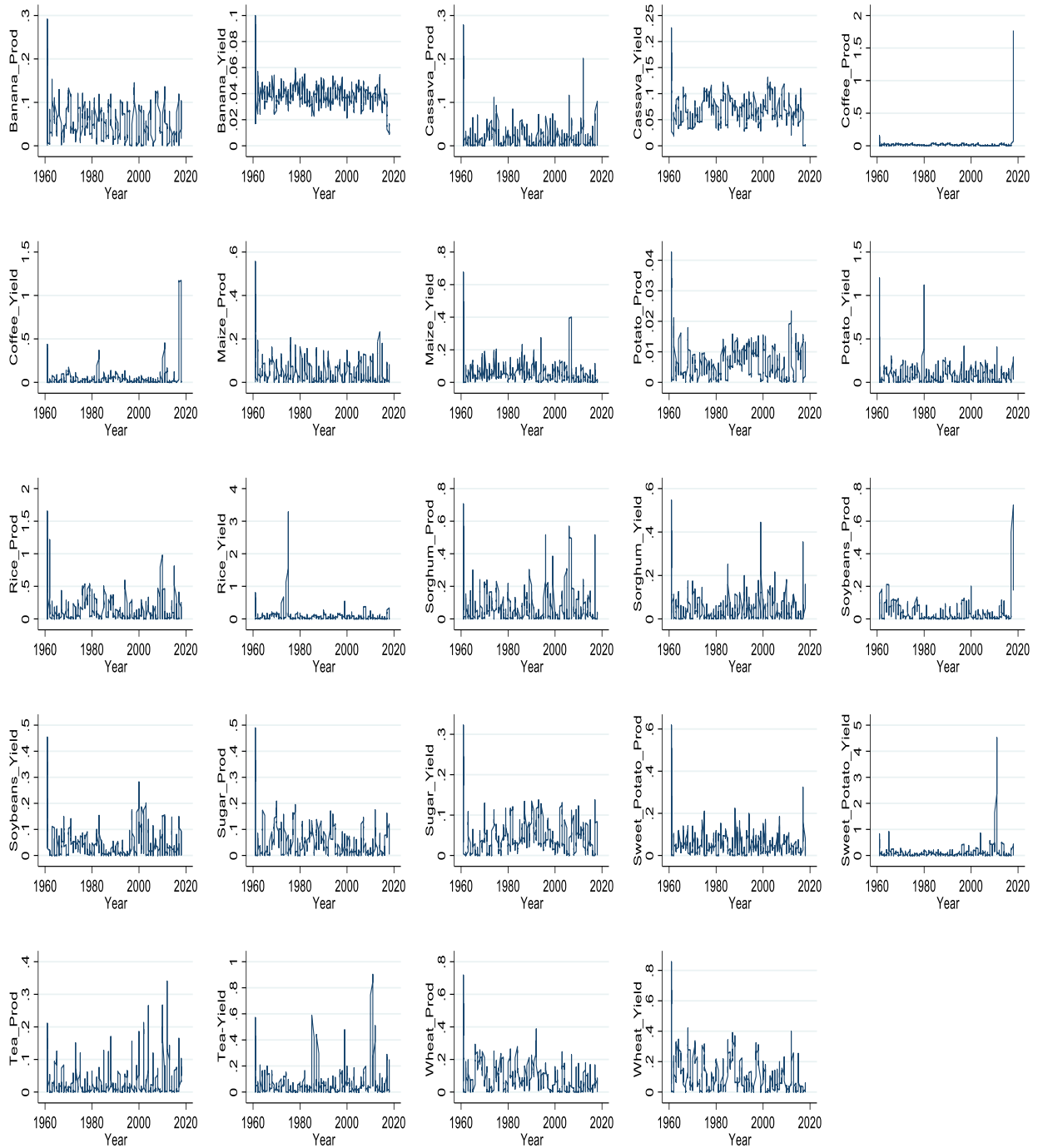


Figure A1: Graphs for yield and rainfall using Clayton copula for Tanzania

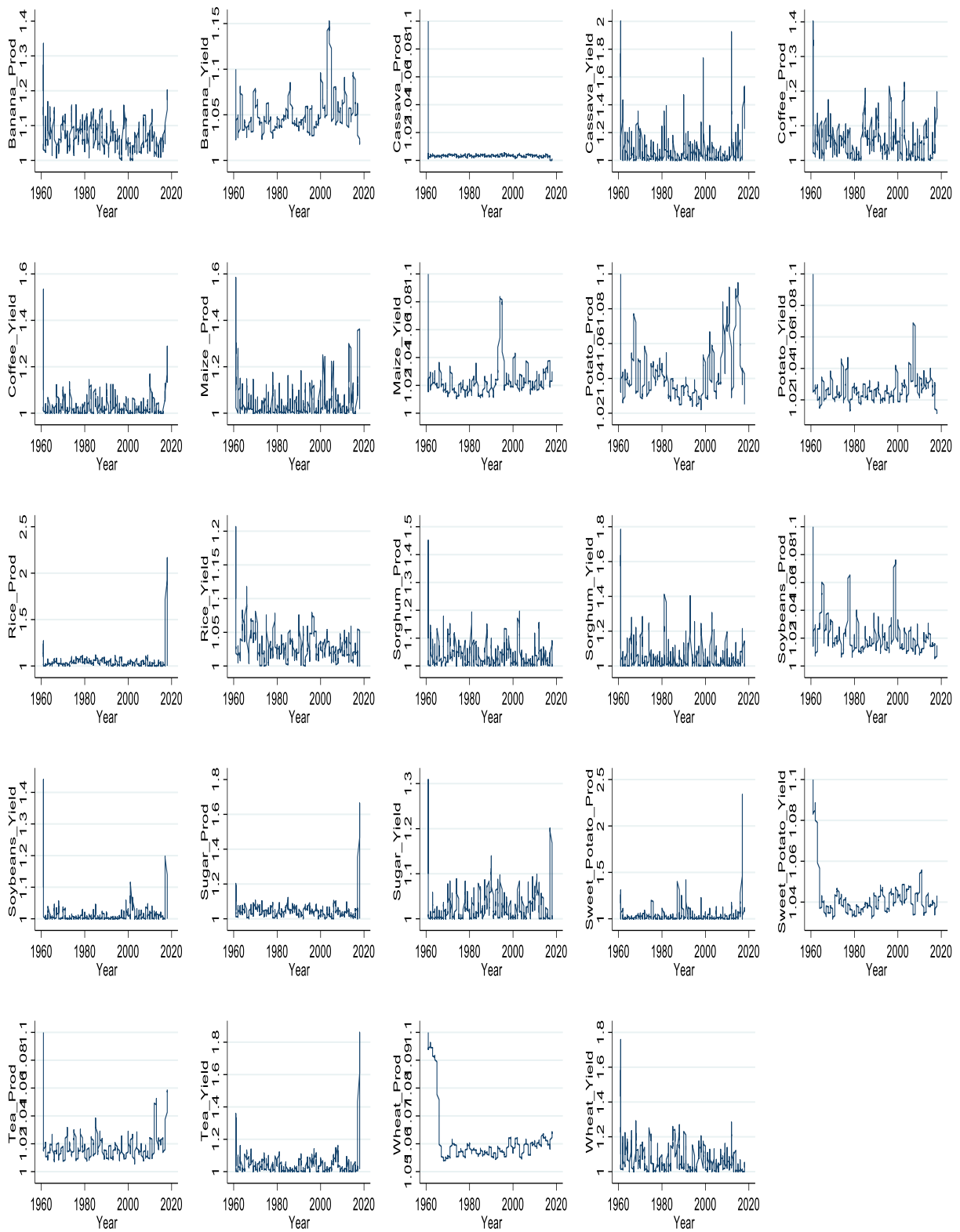


Figure A2: Graphs for yield and temperature using Gumbel copula for Tanzania

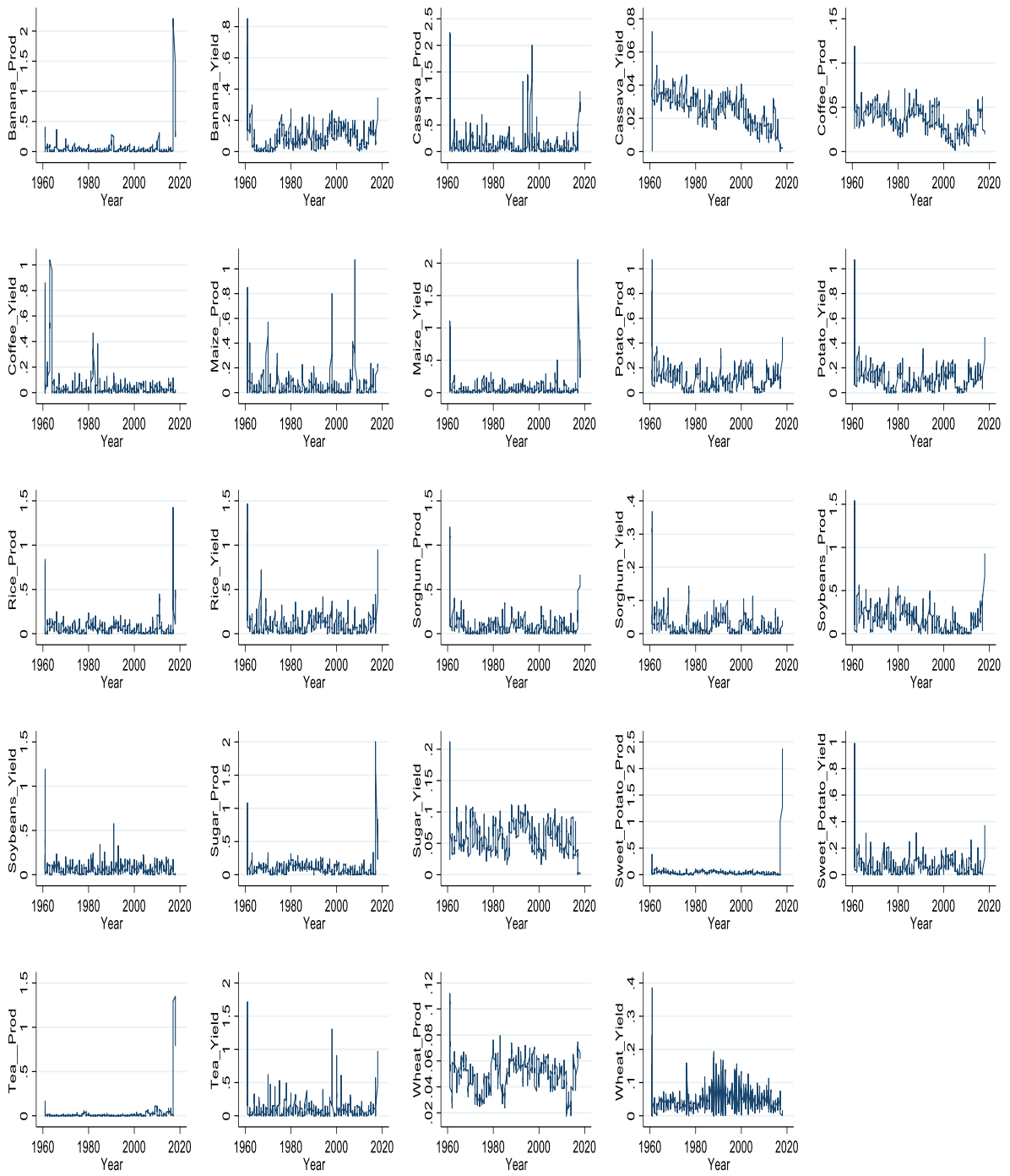


Figure A3: Graphs for yield and rainfall using Clayton copula for Uganda

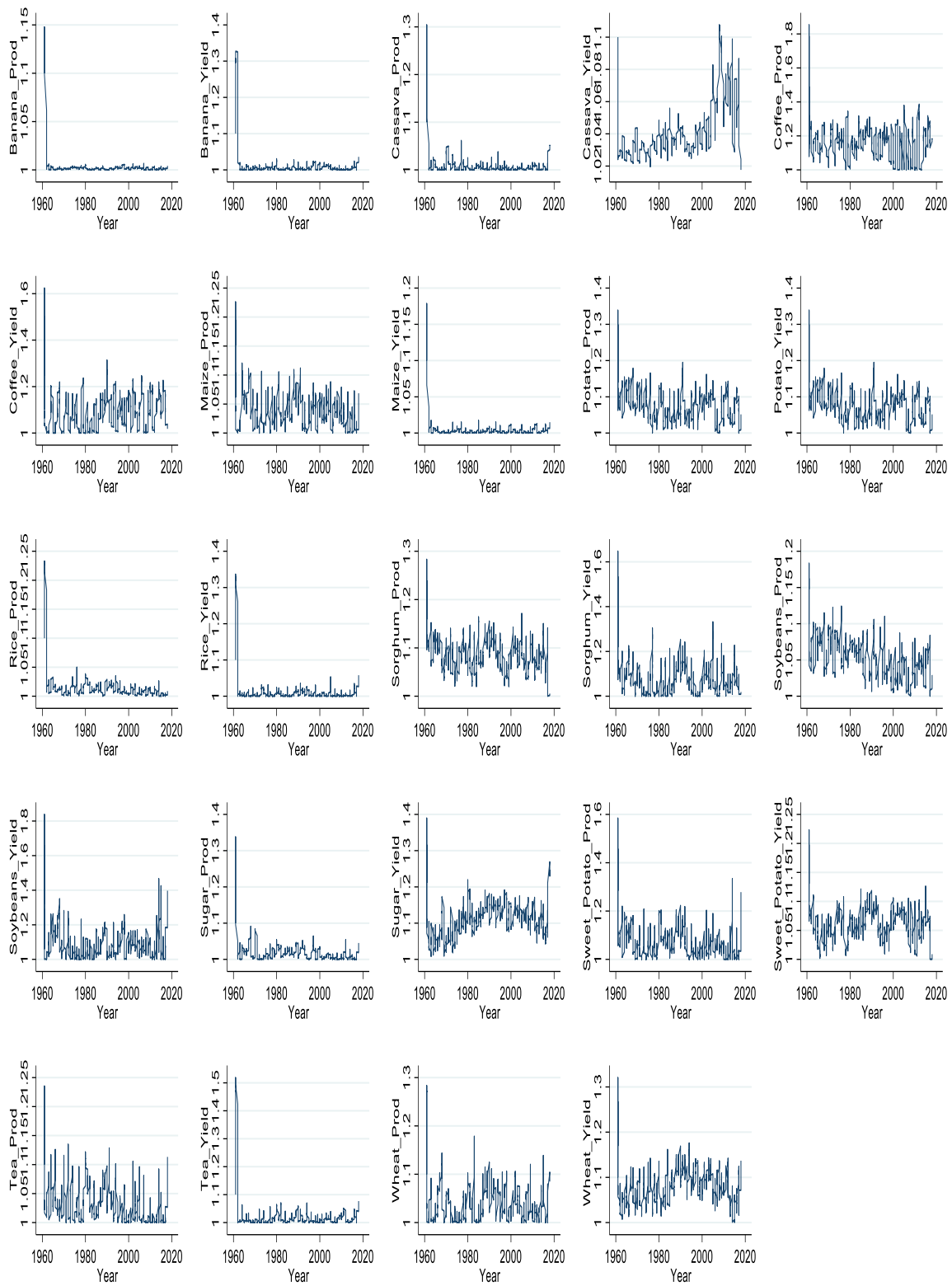


Figure A4: Graphs for yield and temperature using Gumbel copula for Uganda