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Effect of Climatic and Non-Climatic Factors on Cassava Yields in Togo: Agricultural Policy Implications

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Abstract: This paper examines the effects of climatic and non-climatic factors on cassava yields in Togo using an Autoregressive Distributed Lag (ARDL) modelling approach and pairwise Granger Causality tests. Secondary data on production statistics, rural population, climate variables, prices and nominal exchange rate for the period 1978–2009 are used. Results for estimated short- and long-run models indicate that cassava yield is affected by both 'normal' climate variables and within-season rainfall variability. An inverse relationship is found between area harvested and yield of cassava, but a significant positive and elastic effect of labour availability on yield in the long run. Increasing within-lean-season rainfall variability and high lean-season mean temperature are detrimental to cassava yields, while increasing main-season rainfall and mean-temperature enhance cassava yields. Through Granger Causality tests, a bilateral causality is found between area harvested and yield of cassava, and four unidirectional causalities from labour availability, real producer price ratio between yam and cassava, main-season rainfall and lean-season mean temperature to cassava yields. Based on the findings from this study, investment in low-cost irrigation facilities and water harvesting is recommended to enhance the practice of supplemental irrigation. Research efforts should as well be made to breed for drought, heat and flood tolerance in cassava. In addition, coupling area expansion with increasing availability of labour is advised, through the implementation of measures to minimize rural–urban migration.

Keywords: cassava; 'Cassava belt'; yield response; Autoregressive Distributed Lag modelling; Granger Causality; Togo

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1. Introduction

A high number of climate impact and yield response studies in Africa and other developing countries predict declines in the yield of major staple crops by the mid- to late 21st century due to climate change, but a more resilient response of cassava to future climatic shocks (e.g., see [1–6]). This indicates a high potential for cassava to adapt to a harsh future climate and serve as a food security crop under such conditions, thereby minimizing the national food insecurity burden. Grown basically for its tuberous roots, cassava is a staple for more than 800 million people worldwide [7], and is the third most important source of calories in the tropics after rice and maize [8]. Well known for its low input requirement and high resilience to unfavourable production conditions, cassava has a high output of energy per area cultivated. (This makes cassava a strategic crop for overcoming hunger) [9], and it is easy to cultivate on marginal lands [4,10,11]. In addition, cassava has a lower risk of crop failure (compared to crops like rice, maize, groundnut, tomatoes, peppers and other vegetables), and serve as a potential feedstock for many industries (through the use of starch for pharmaceutical, textile and adhesive purposes), a famine reserve (flexibility in harvesting) and a cash crop [7,12].

These beneficial attributes have earned the crop research, investment and political attention over the past eight decades [13].

Despite the benefits derived from the crop, the growth of the cassava sub-sector in major production regions has been hindered by two primary constraints; pests and diseases (specifically the Africa Cassava Mosaic Virus Diseases (ACMV) and the Cassava Brown Streak Virus (CBSV)) and low yields [13,14]. Addressing these two constraints has been the major focus of research, investment and political efforts made towards promoting cassava production at the local, national and global scales [13]. Although such efforts may have yielded some encouraging results in controlling cassava-related pests and diseases in major production zones worldwide, the cassava yields observed in West and Central Africa are far below the achievable. Compared to yields of 90 tons per hectare observed under ideal growing conditions in Colombia [15,16], and recorded yields (for the year 2013) of 21.8–22.5 tons/hectare in countries like Thailand and Indonesia [11], the yields observed by subsistence farmers in West and Central Africa are generally within the range of 8–12 tons [17–19]. This is far below achievable yields of 75–90 tons of fresh roots per hectare in cassava mono-crop [10,20] and 25–50 tons/hectare in some mixed/mono-cropping (experimental) systems across West and Central Africa [21,22].

Despite the wide yield gap in the majority of the countries in the region, a significant number of countries observed annual growth in cassava yields over the five decades between the years 1964 and 2013. As shown in Figure 1, countries like Benin, Cameroon, Chad, Côte d'Ivoire, Ghana, Mali, Niger, Senegal and Sierra Leone observed annual increments of more than 1% between the years 1964 and 2013, while countries like Nigeria and Guinea observed minor annual growth. In contrast, Togo, the country with the highest cassava yields during the period 1964–1973, observed an annual decline of 2.60% between the years 1964 and 2013. From a leading position in productivity during past decades, Togo is now one of the countries with the lowest cassava yields in the sub-region.

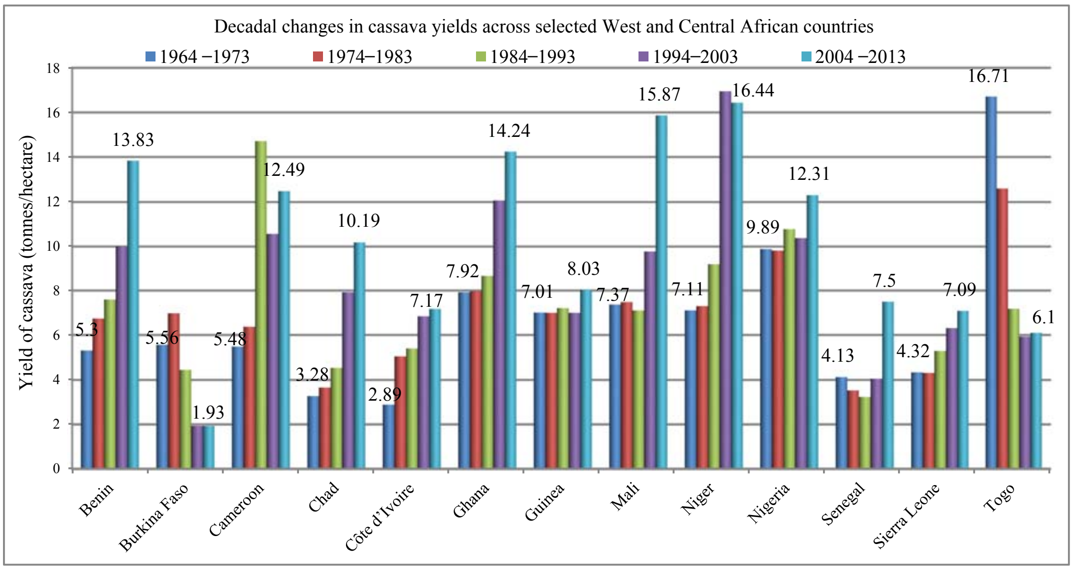

Figure 1. Decadal changes in cassava yields across selected West and Central African countries. Source: Author's construct with data from FAOSTAT (2014). Annual growth rates for the period 1964–2013: Benin (2.34% ***), Burkina Faso (−3.43%, ***), Cameroon (2.08%, ***), Chad (3.00%, ***), Côte d'Ivoire (2.14%, ***), Ghana (1.61%, ***), Guinea (0.27%, ***), Mali (1.75%, ***), Niger (2.50%, ***), Nigeria (0.49%, ****), Senegal (1.28%, ***), Sierra Leone (1.42%, ***), Togo (−2.60%, ***).

Based on the role played by the crop in the Togolese diet (as a major staple), in national agricultural production and trade, as the second most important crop in the country after maize [23], and accounting for approximately 15% of total dietary energy supply (*and 59.14% of dietary energy supply by starchy* *roots* (*computed by the author using food supply data from FAOSTAT for the period 2001–2010)*) and 11% of gross value of agricultural production (*in constant 2004–2006, 1000 Int. $*), this declining trend in the yield of cassava in the country is deemed worrisome. For the crop to stand a chance of contributing significantly to the future food needs of the country under the anticipated harsher future climate, there arises a need to address the current productivity challenge through an identification of the major factors that limit cassava yields in the country, and the implementation of measures to address present limitations. To inform policy formulation and investment decisions in Togo in this regard, several research efforts have been made. Emphasis has, however, so far been placed on the effects of biotic (e.g., weeds, pests and viral diseases) determinants of cassava productivity (e.g., [23–25]), with very little (if anything) done to ascertain the effects of abiotic (climatic), socioeconomic and policy determinants. Addressing the low productivity challenge requires not only information on biotic influences, but also on the effect of other relevant determinants of yields. This study seeks to bridge the current knowledge gap on the effect of climatic and non-climatic factors on yields of cassava in Togo. An autoregressive Distributed Lag (ARDL) modelling approach and pairwise Granger Causality tests are used for the analysis. Secondary data on production statistics, rural population, climate variables, and price and policy-related variables for the period 1978–2009 are used. In summary, the study seeks to:

1. Analyze the yield response of cassava to changes in climatic and non-climatic factors in Togo; and
2. Inform policy and investment decisions on the measures needed to boost productivity of cassava in the country.

In Section 2, some statistics on output, acreage and yield of cassava over the five decades between 1964 and 2013 are provided to reveal decadal trends. Section 3 provides a summary (review) of findings from previous studies. Methods (study area and analytical framework) are covered in Section 4, results and discussion in Section 5, and conclusion and policy recommendations in Section 6.

2. Evolution of Cassava Production, Area and Yields in Togo

Prior to the prolonged drought of 1982, cassava production in Togo was basically driven by increments in yield and productivity of crop fields (resulting from proper management of the smaller parcels of land owned by farmers and from consolidation). During this period, greater shares of lands were devoted to the production of staples like maize, sorghum and millet, and to economic legumes and cash crops like groundnuts, cowpea, common beans, yam and cotton. Although cassava was and continues to be a key component of Togolese diets, the area allocated to production of the crop during the period 1964–1973 decreased at a rate of 0.52% per annum (not significant), while yields increased at an annual rate of 1.84% (significant at the 10% level). As shown in Table A1 in the appendix, however, the annual increment (1.31% per annum) observed in production during this period was not significant. Due to erratic rainfall in the late 1970s and prolonged drought in 1982, the need to expand the area devoted to cassava production (as a famine resort) became a priority in the country's policy and in the seasonal cropping decisions of farming households. From an insignificant annual decline of 0.52% (during the period 1964–1973), the area allocated to cassava production increased at a significant annual rate of 21.05% during the period 1974–1983, with this increase driven primarily by a sharp rise in the area harvested, from 43,100 hectares in 1981 to 108,700 hectares in 1982. The increasing cost of production following such a rise, coupled with rural–urban migration (as a coping strategy by farm households, thereby reducing agricultural labour availability) and mismanagement of cassava fields resulted in a sharp decline in yields from 8.63 tons/hectare in 1981 (although higher yields were observed in the 1960s and early 1970s) to 3.38 tons/hectare in 1982 (the lowest observed in the country so far). In contrast to the 21.05% annual increase in area of cassava harvested during the period 1974–1983, yields decreased at a significant rate of 18.29% per annum. This significant mismatch between area harvested and yields led to an insignificant decline of 1.09% per annum in cassava production. Area harvested of cassava has since then, specifically over the decades 1994–2003 and

2004–2013, manifested increasing trends, with an annual increment of more than 3%. Yields, on the other hand, fluctuated over the decades after the period 1974–1983 (increasing significantly at a rate of 1.02% per annum only in the last decade (2004–2013)). Increasing at a significant annual rate of more than 4% during the periods 1994–2003 and 2004–2013, production has taken after the trends in area harvested. Low yields of cassava in the country have been attributed, among other causes, to the use of low-yield varieties, a high incidence of pest and diseases, declining soil fertility, a lack of good planting materials, and poor marketing, which precludes effective promotion of the crop [26].

3. Yield Response of Cassava: A Review

Regarded as one of the world's most important food crops, cassava is mostly cultivated as a security crop due to its strong abiotic resistance characteristics [4], flexibility in harvesting [7] and ability to produce appreciable yields on marginal lands with low input [10,11] compared to crops like maize, rice, and groundnut. The crop is, however, exposed throughout its production cycle to diverse biotic, abiotic, policy and management constraints. Depending on the type of constraint to which the crop is exposed within and between seasons, different yield responses are documented in the literature. In this review, we place sole emphasis on a few of the non-biotic determinants of cassava yields. The crop is generally found to be more resilient under harsher climatic conditions than other staples like maize, sorghum, millet, and groundnut [2,27]. In a study on the impact of climate change on crop yields in sub-Saharan Africa, and under alternative climate change scenarios, Blanc [27] predict yield changes of −19% to +6% for maize, −38% to −13% for millet, and −47% to −7% for sorghum by 2100. Predicted changes in cassava yields are, however, near zero. Floods were found to be detrimental to cassava yields in the base regression. Schlenker and Lobell [2] predict yield losses of −22%, −17%, −17%, −18%, and −8% respectively for maize, sorghum, millet, groundnut and cassava in sub-Saharan Africa. These predictions show that cassava is relatively more resilient to changes in climatic conditions than most of the priority crops in sub-Saharan Africa. Despite its resilience, a report on crop substitution behaviour among food crop farmers in Ghana found a significant negative effect of increasing maximum temperature on cassava yields, but a significant positive effect of rainfall and increasing minimum temperature [28]. A positive effect of rainfall on cassava yields is also reported by [29] for the Guinea Savanna part of Nigeria. In contrast to the findings by [28,29], Emaziye [30] reports a positive effect of increasing temperature on cassava yields in Nigeria, but a negative effect of increasing rainfall. Through cointegration analysis, Mbanasor et al [31] find a positive short-term but negative long-tern effect of rainfall on cassava yields, and a consistent negative effect of temperature in both the short and the long term. Through analysis of sensitivity of crop yield to extreme weather in Nigeria, Ajetomobi [32] finds a negative effect of extreme temperature and rainfall on cassava yield. Whereas a 1% rise in extreme temperature led to only a 0.05% decrease in cassava yield, a 1% increase in rainfall led to a 2.17% decrease in yield.

Despite the significant effects of temperature reported in Nigeria and Ghana, other researchers find very little or no effect of temperature on cassava yields, even when the optimal temperature range is exceeded by 5–10 °C [16,33]. These differences in the effect of temperature on cassava yields reflect regional differences in the sensitivity of cassava to changing local climatic conditions, and necessitate the undertaking of country-specific studies to inform locally relevant policy decisions. In a study by [4], cassava was found to be tolerant to high temperatures and intra-seasonal drought. Exposure of the crop to prolonged drought (of at least two months) during the tuber-formation and root-thickening stages, however, decreases root yields by 32%–60%. This indicates that the ability of cassava to resist the adverse effects of climatic stressors depends on the timing, strength and duration of the event [4]. Most of the impact studies conducted so far have placed more emphasis on the climatic aspects of non-biotic determinants. With the few that looked beyond the climatic aspects, cassava yields reportedly decreased with increasing land area (e.g., [27]). Indicating decreasing marginal land productivity, a 10% increase in the area allocated to cassava production in sub-Saharan Africa caused a 2% decrease in cassava yields [27]. In addition to the effect of increasing land area on crop yields, other researchers (e.g., [28]) report beneficial implications of increasing maize price for cassava through increased allocation of land for cassava production in Ghana. The increasing price of cassava also prompted farmers to allocate more land for maize. These results indicate some form of complementary association between maize and cassava in Ghana. In contrast to this, a study by [34] observed a decline in the output of maize with an increasing price of cassava, but an increase in maize output with an increasing price of maize and yams. This indicates a complementary association between maize and yam, but a competitive association between maize and cassava. Findings from the various articles reviewed in this section show a general contextual nature of response of cassava to climatic stressors. Information on the effect of non-climatic (and non-biotic) stressors at a more macro level is quite limited.

4. Methods

4.1. Study Area

As shown in Figure 2, Togo is a West African country that shares borders with Ghana in the west, Burkina Faso in the north, the Republic of Benin in the east, and the Gulf of Guinea in the south. The country's economy is agriculture-driven, with crops like coffee, cocoa, and cotton dominating in income generation via exports, while yam and cassava dominate in contribution towards the total gross value of agricultural production (21.48% for yam and 10.67% for cassava). Agriculture accounts for approximately 40% of GDP (50% of the country's export earnings) and employs about 70% of the country's population [35]. Togo's climate varies from tropical in the south to savanna in the north. The country has five economic regions, namely the Savanes (Savannah region), the Kara region, the Central region, the Plateaux region, and the Maritime region. The last two regions cover 40.2% of the national land area, 68.56% of the area harvested for cassava, and 69.64% of national cassava output (based on CountrySTAT data for 2001–2011). The first three regions have a unimodal rainfall regime, while the last two have a bimodal distribution. The growing period for the unimodal zone stretches from May to November. In the bimodal zone, the main season covers March to July (*planting and vegetative period for cassava, yam and other roots and tubers, and the growing period for major cereals and legumes*), while the lean season covers September to November (*tuber formation period for cassava based on cropping calendar for the zone*). Although all five regions are exposed to common climatic threats like violent winds, erosion, late onset, poor distribution of rains, droughts and flooding [35], the distribution of major crops/livestock produced in the country varies by region.

Figure 2. Map of study area.

Based on information gathered from [21], and as shown in Table A2 (in the appendix), cassava production takes place mostly in the Maritime and western Plateaux regions, while yam cultivation takes place in the yam belt (the three regions in the unimodal zone) and in the western Plateaux. Traditional staples like millet and sorghum are produced mainly in the unimodal rainfall zone, while the main legumes, rice, maize and cash crops like cotton are produced across zones. The country has 10 primary synoptic weather stations, with six in the unimodal zone (in Mango, Dapaong, Niamtougou, Kara, Sokode, and Sotouboua) and four in the bimodal zone (in Atakpame, Kouma-Konda, Tabligbo and Lome). Cassava production and yields in the country are, however, heavily influenced by climatic conditions in the last three stations of the bimodal rainfall zone. Assessment of the effect of climatic factors on cassava yields in the present study is therefore based on average climatic conditions for the three highlighted synoptic stations in the south (see Figure 2).

4.2. *Changing Climatic Conditions for the 'Cassava Belt' and Yield of Cassava in Togo*

To emphasize the exclusion of climate data for the eastern Plateaux in the current study, the cassava producing areas are henceforth referred to as the 'Cassava belt'. Between the years 1978 and 2009, rainfall for both the main and lean seasons fluctuated, depicting no obvious trends. Non-significant annual declines of −0.399% and −0.290% are estimated for the main- and lean-season rainfall, respectively. Main- and lean-season mean temperatures, however, increased at significant rates of 0.026 °C and 0.032 °C per annum, respectively. Total rainfall in the main season ranged between 488.07 mm (in the year 2000) and 978.37 mm (in the year 1989), with a mean value of 694.58 mm and coefficient of variation estimate of 18.43%.

From Figure 3, the total rainfall in the lean season ranged between 167.07 mm (in the year 1996) and 461.77 mm (in the year 1980), with a mean of 331.64 mm and a coefficient of variation estimate of 22.30%. This indicates a relatively higher variability of rainfall in the lean season. Main-season mean temperature ranged between 25.87 °C (in the year 1978) and 27.82 °C (in the year 1998), while a range of 25.48 °C (in 1978) to 26.76 °C (in 2005) is recorded for the lean season. Mean values of 26.79 °C (with standard deviation of 0.39 °C) and 26.16 °C (with a standard deviation of 0.38 °C) are recorded for the main and lean seasons, respectively. We find no obvious visual correlation (in terms of trends) between the seasonal rainfall measures and yield of cassava, but, rather, opposing trends between changes in seasonal temperature and yield of cassava. Whereas increasing trends are observed for the main- and lean-season temperatures, the yield of cassava decreased at an annual rate of 0.12 tons/hectare over the period 1978–2009.

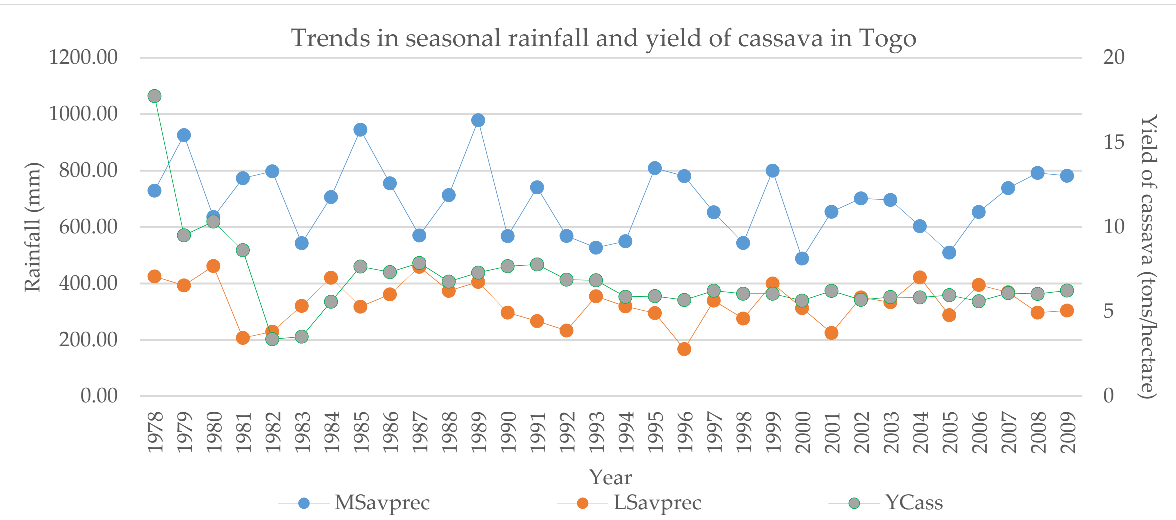

Figure 3. *Cont.*

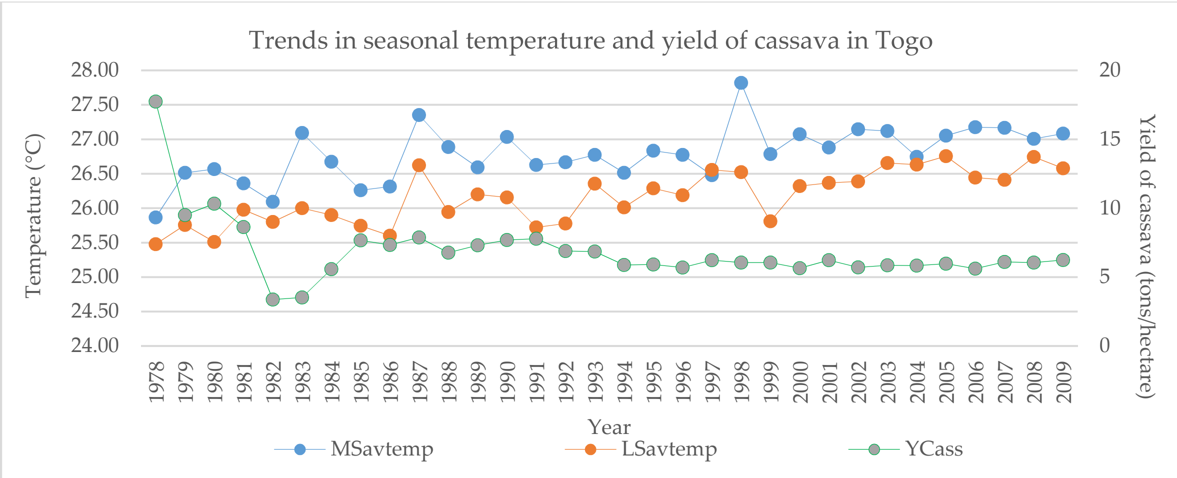

Figure 3. Rainfall and temperature trends in the 'Cassava belt' of Togo. Source: Author's construct with data from the National Meteorological Service. NB: MSavprec—rainfall for the main season; LSavprec—rainfall for the lean season; MSavtemp—mean temperature for the main season; LSavtemp—mean temperature for the lean season; YCass—Yield of cassava.

4.3. Analytical Framework

4.3.1. Model

Findings from agricultural supply response studies serve as a useful guide in local, regional, national and global food policy formulation and agribusiness investment decisions. This study places emphasis on analyzing the response of cassava yield to climatic and non-climatic factors in Togo. Based on documented evidence on determinants of cassava yields in the literature and observed realities on the ground in the current study area, the following yield response function is assumed as a base model for this study:

$$YCass = f\left(\begin{array}{c} ACass, Rulpop,\ RPMaiCass, RPYamCass, RPBeaCass, Exr, MSavprec,\ LSavprec, \\ MSavprec\_Var, \\ LSavprec\_Var,\ MSavtemp, LSavtemp \end{array}\right) \quad (1)$$

From Equation (1), the yield of cassava (*YCass*) is assumed to be a function of the area of cassava harvested (*ACass*); the total rural population (*Rulpop*—a proxy for labour availability); the real producer price ratios between maize and cassava (*RPMaiCass* (RP_{Mai_t}/RP_{Cass_t}, RP_{Mai_t} : $real\ producer\ price\ of\ maize\ at\ time\ t$, RP_{Cass_t} : $real\ producer\ price\ of\ cassava\ at\ time\ t$), yam and cassava (*RPYamCass* ($RP_{Yam_t}/RP_{Cass_t}, RPYam_t$: $real\ producer\ price\ of\ yam\ at\ time\ t$)), and common beans and cassava (*RPBeaCass* ($RP_{Bea_t}/RP_{Cass_t}, RP_{bea_t}$: $real\ producer\ price\ of\ common\ beans\ at\ time\ t$)); the nominal exchange rate (*Exr*); the total volume of rainfall for the main season (*MSavprec*); the total volume of rainfall for the lean season (*LSavprec*), the within-main-season rainfall variability (*MSavprec_Var* (*measured as the standard deviation of the monthly (months in the main season) means expressed as a percentage of their respective seasonal means* [36]; a similar definition is used for the lean season, but using months in the lean season); the within-lean-season rainfall variability (*LSavprec_Var*); the main-season mean temperature (*MSavtemp*); and the lean-season mean temperature (*LSavtemp*).

In line with previous crop yield response studies in Africa (e.g., [36,37]), we assume a Cobb–Douglas functional form for the base model, and rewrite Equation (1) as follows:

$$\begin{gathered} lnYCass_t = \beta_0 + \beta_1 lnACass_t + \beta_2 lnRulpop_t + \beta_3 lnRPMaiCass_t + \\ \beta_4 lnRPYamCass_t + \beta_5 lnRPBeaCass_t + \beta_6 lnExr_t + \beta_7 lnMSavprec_t + \\ \beta_8 lnLSavprec_t + \beta_9 lnMSavprec\_Var_t + \beta_{10} lnLSavprec\_Var_t + \beta_{11} lnMSavtemp_t + \\ \beta_{12} lnLSavtemp_t + \mu_t, \end{gathered} \quad (2)$$

where ln represents a natural logarithm, t is a representation of year (time), and μ represents the error term.

In analyzing the yield response of crops, several approaches have so far been documented in the literature, including simple Ordinary Least Squares (OLS) estimation of multiple regression (e.g., [36]), Nerlovian adjustment cum adaptive expectation model [38], and cointegration analysis (e.g., [39,40]). In this study, emphasis is placed on cointegration analysis. In testing for the existence of valid relationships under a cointegration framework, three principal approaches have been adopted. These are the two-step residual based procedure for testing a null of no-cointegration (Engle–Granger cointegration test) [41], the system-based reduced rank regression approach (Johansen cointegration test) [42,43], and the bounds testing (Autoregressive Distributed Lag model) approach [44]. The Autoregressive Distributed Lag (ARDL) approach is used for the current analysis due to its efficient performance in analyzing relationships in small samples and its ability to incorporate variables with mixed order of integration. Unlike the Engle–Granger approach or the Johansen cointegration test, the ARDL yields consistent estimates of long-run coefficients irrespective of the order of integration of the variables included in the model [44] and even when some of the regressors are endogenous [45]. All variables are, however, expected to be either $I(1)$ (variables that are non-stationary at level, but become stationary on first difference), or $I(0)$ (variables that are stationary at level) or both. The ARDL approach involves the following four primary steps.

1. Estimation of a specified model based either on automatically selected lags of the dependent variables and regressors or based on fixed lags by the researcher. Appropriate number of lags and best model among evaluated models under the automatic selection are based on one of four model selection criteria, namely Akaike information criterion (AIC), Schwarz criterion (SIC), the Hannan–Quinn criterion (HQ), and selection based on adjusted R-squared.
2. After estimating the base model, a Bounds test is carried out to test the null hypothesis of non-existence of a long-run relationship among the variables in the base model. Rejecting the null (based on F-test and critical value Bounds for $I(0)$ (lower bound) and $I(1)$ (upper bound)) indicates the existence of long-run relationship among the variables, irrespective of the order of integration of the variables. The null hypothesis is rejected only if the F-statistics lies above the upper bound at the 5% significance level (although 10% could be used in some cases). Failing to reject the null implies the non-existence of co-integration. By the Granger representation theorem [41], a confirmation of cointegration among variables implies the existence of an error correction model (ECM) that describes short-run dynamics and/or adjustment of the cointegrated variables towards their long-run equilibrium values. The existence of cointegration is validated by a significant negative coefficient of an error correction term in the ECM. In the absence of cointegration, output for the base estimation is synonymous with output of a simple Ordinary Least Squares estimation of the specified model with the inclusion of stated lags.
3. Having confirmed the existence of long-run relationships after the Bounds test, short-run (cointegrating form) and long-run coefficients are estimated from the base model using an error correction mechanism that ensures appropriate adjustment towards long-run equilibrium whenever deviations are observed in the system.
4. The efficiency of the estimated coefficients is assessed based on diagnostic tests for the classical Gaussian assumptions of linear regression models (emphasizing normally distributed errors,

lack of serial correlation and lack of heteroskedasticity). The appropriateness of the model specification is also assessed using a Ramsey RESET test, while the reliability and stability of the coefficients are assessed using CUSUM and CUSUM of Squares tests.

For further details of the mechanics behind the estimation of relevant parameters under the ARDL framework, and as documented by [44,46], see Section AE 1 in the appendix. Following a confirmation of long-run relationships by the Bounds test, Equation (2) is re-parameterized to produce the following error correction representation of the ARDL model used in this study:

$$\begin{aligned}\Delta \ln YCass_t = \Gamma_0 + \textstyle\sum_{l=1}^{L} \Gamma_1 \Delta \ln YCass_{t-i} + \sum_{m=1}^{M} \Gamma_2 \Delta \ln ACass_{t-i} + \sum_{m=1}^{M} \Gamma_3 \Delta \ln Rulpop_{t-i} + \\ \textstyle\sum_{m=1}^{M} \Gamma_4 \Delta \ln RPMaiCass_{t-i} + \sum_{m=1}^{M} \Gamma_5 \Delta \ln RPYamCass_{t-i} + \sum_{m=1}^{M} \Gamma_6 \Delta \ln RPBeaCass_{t-i} + \\ \textstyle\sum_{m=1}^{M} \Gamma_7 \Delta \ln EXR_{t-i} + \sum_{m=1}^{M} \Gamma_8 \Delta \ln MSavprec_{t-i} + \sum_{m=1}^{M} \Gamma_9 \Delta \ln LSavprec_{t-i} + \\ \textstyle\sum_{m=1}^{M} \Gamma_{10} \Delta \ln MSavprec\_Var_{t-i} + \sum_{m=1}^{M} \Gamma_{11} \Delta \ln LSavprec\_Var_{t-i} + \\ \textstyle\sum_{m=1}^{M} \Gamma_{12} \Delta \ln MSavtemp_{t-i} + \sum_{m=1}^{M} \Gamma_{13} \Delta \ln LSavtemp_{t-i} + \gamma ECM_{t-1}.\end{aligned} \tag{3}$$

From Equation (3), Δ represents the first difference operator, Γ_0 is the intercept term for the cointegrating equation, Γ_i represents short-run coefficients, ECM_{t-1} is the error correction term, while γ reflects the speed at which deviations from long-run equilibrium are corrected for in the short run. Variables are defined as in Equation (2). Although a trend variable was included in the initial specification and estimations of the base model to help control for the effect of technological investment and other policy initiatives on cassava yield, this variable was dropped in the final estimation. The coefficient for the trend variable was not significant at any reasonable level (a *p*-value of 0.6949 was observed). In addition, including a trend variable in the model selected for this study led to a reduction in the predictive power of the model (based on a reduced value of the Adj. R-squared and F-statistic, and based on estimates for the AIC, SIC and HQ). Moreover, estimates for the model without the trend variable were found to be more stable and reliable (based on CUSUM and CUSUM of Squares tests). The ARDL model is estimated in EViews 9 (SV).

4.3.2. Pairwise Granger Causality Test

Upon a presumption that a correlation between two variables does not necessarily imply causation, a pairwise Granger Causality test is carried out after estimation of the ARDL model to ascertain the direction of causality among variables. This is a statistical hypothesis test for determining whether one time series is useful in forecasting another [47]. A given series X is said to Granger-cause Y, *if and only if* it can be proven through a series of tests (*t*-tests and *F*-test) on lagged values of X and Y that the values of X provide statistically significant information about future values of Y [48,49]. Specification of the appropriate equations for establishing such causalities depends on the order of integration of the variables. Further details on the mechanics behind the Granger Causality test are provided in Section AE 2 in the appendix. In selecting the appropriate number of lags to use for the causality test, and per proposition by the EViews user's guide [50], the most appropriate lag length is one that "corresponds to reasonable beliefs about the longest time over which one of the variables could help predict the other". This proposition is based on the presumption that the theory is couched in terms of relevance of all past information. In this regard, and based on the realities on the ground in the study area, we use a lag length of 5 for the pairwise Granger causality test.

4.3.3. Data

Data on yield, output, acreages and producer prices for the respective crops were gathered from the agricultural production and price database of FAO (FAOSTAT) in October 2014. After gathering these data, a 2010 consumer price index series from IRRI's (International Rice Research Institute) World Rice Statistics database was used to convert the price variables from their original nominal values into real values to correct for inflation. Data on exchange rate and rural population were gathered from the World Bank's Development Indicators database and from theGlobalEconomy.com [51]. For weather variables, data supplied by the National Meteorological Service for the three synoptic stations in the 'Cassava belt' were used to compute representative values for the entire belt. Data for each of the variables covers the period 1978–2009.

5. Results and Discussion

5.1. Unit Root Test of Variables

Although pre-testing of the variables to ascertain their respective order of integration is deemed a less vital task in ARDL analysis, it is deemed a necessity for the pairwise Granger causality test. Along this line, we first test the respective series for stationarity using the Phillips–Perron (PP) unit root test. This test is basically a Dickey–Fuller test that has been made robust to serial correlation by using the Newey–West [52] heteroskedasticity and autocorrelation consistent matrix estimator. As shown in Table 1, except for the exchange rate, all data series are found stationary at level. The data series for exchange rate becomes stationary on first difference. This renders the exchange rate an $I(1)$ variable and all other variables $I(0)$. Based on results for the unit root test, levels of the $I(0)$ variables are used for the pairwise Granger causality test, while the first differenced form of the exchange rate is used for testing the causation between yield and exchange rate.

Table 1. Results of unit root test.

Variable	Phillips–Perron Test (Adj. t-Stat)		
	Level	First Diff.	Status
ln YCass	−6.1981 ***		$I(0)$
ln ACass	−3.2168 **		$I(0)$
ln Rulpop	−3.7992 ***		$I(0)$
ln RPMaiCass	−4.9087 ***		$I(0)$
ln RPYamCass	−3.6271 **		$I(0)$
ln RPBeaCass	−3.6846 ***		$I(0)$
ln Exr	−1.8033	−4.6475 ***	$I(1)$
ln MSavprec	−5.3801 ***		$I(0)$
ln LSavprec	−4.9648 ***		$I(0)$
ln MSavprec_Var	−5.4896 ***		$I(0)$
ln LSavprec_Var	−13.638 ***		$I(0)$
ln MSavtemp	−5.0881 ***		$I(0)$
ln LSavtemp	−3.1981 **		$I(0)$

NB: Intercept included at level; no trend nor intercept on first difference; sig. ** 5%, *** 1%.

5.2. Short- and Long-Term Relationships

We commenced analysis with the selection of an appropriate number of lags and the best model to use as the estimation equation. In this regard, several lags were used in the initial estimations. Given the number of explanatory variables used in this study, the permissible maximum number of lags for the regressors was 1, while that for the dependent variable was 5. Best models for 1 up to 5 lags of the dependent variable and 1 for the regressors were compared. Based on F-statistic, Adj-R^2, and estimates for Akaike information criterion (AIC), Schwarz information criterion (SIC), and Hanna–Quinn criterion (HQ), an ARDL (3,0,0,0,0,0,0,0,0,0,0,0,0) was selected as the best model. From Table A3 in the appendix, a total of about 91.46% of the variations in cassava yields in Togo is explained by regressors in the base model. To ascertain whether the observed estimates in the base model reflect the true relationships, a Bounds test was performed. As shown in Table 2, the null hypothesis of no long-term relationships is rejected at the 5% significance level. This indicates a need to incorporate short-term dynamics and correct for deviations from the long-term equilibrium through incorporation of an error correction mechanism in the model.

Table 2. Bounds test (null hypothesis: no long-term relationship exists).

Test Statistic	Value	K
F-statistic	5.8722	12
Critical Value Bounds		
Significance	I0 Bound	I1 Bound
10%	4.78	4.94
5%	5.73	5.77
2.5%	6.68	6.84
1%	7.84	4.05

Cointegrating and long-term forms of the base model were therefore estimated. As shown in Table 3, we note that a total of about 77.56% of deviations from the long-term equilibrium are corrected in the short term. This high speed of adjustment reflects a system with low persistence of high and low values of the dependent variable. We observe a consistent negative response of cassava yields to increasing area harvested of the crop in both the short and the long term. This is in conformity with documented evidence of an inverse relationship between farm size and productivity (e.g., [27,53,54]). Reflecting decreasing marginal productivity of land [27], this observed inverse relationship between area harvested of cassava and yield of the crop is attributed in greater part to a potential increase in the cost of production with increasing area and to a high land/labour ratio [53]. Keeping labour and other relevant variables constant, increasing the area of cassava harvested increases the land/labour ratio and precludes the timely undertaking of relevant cultural and management practices, thereby reducing the intensification of production. In addition, the need for disease and pest control and the costs involved are likely to increase with the area harvested. A 10% increase in area of cassava harvested leads to 9.45% and 11.03% decreases in the yield of the crop in the short and long term, respectively.

Table 3. ARDL Cointegrating and long-term estimates. (Original dep. Variable: ln YCass; Selected Model: ARDL (3,0,0,0,0,0,0,0,0,0,0,0,0); Included observation: 29).

Cointegrating Form			
Variable	**Coefficient**	**Std. Error**	**Prob**
D (ln YCass (-1))	0.0945	0.0728	0.2167
D (ln YCass (-2))	−0.1632 **	0.0616	0.0201
D (ln ACass)	−0.9447 ***	0.0675	0.0000
D (ln Rulpop)	0.2665	2.6601	0.9218
D (ln RPMaiCass)	0.1543 ***	0.0495	0.0082
D (ln RPYamCass)	0.6321 ***	0.1613	0.0018
D (ln RPBeaCass)	−0.4193 ***	0.0831	0.0002
D (ln Exr)	0.2791 ***	0.0915	0.0093
D (ln MSavprec)	0.2021 ***	0.0590	0.0045
D (ln LSavprec)	−0.0049	0.0554	0.9316
D (ln MSavprec _Var)	0.0384 *	0.0216	0.0988
D (ln LSavprec _Var)	−0.0894 ***	0.0267	0.0052
D (ln MSavtemp)	1.9443 *	0.9887	0.0710
D (ln LSavtemp)	−4.7798 ***	1.0950	0.0008
Intercept	6.1557 ***	1.5789	0.0018
ECT (-1)	−0.7756 ***	0.2033	0.0021

Table 3. *Cont.*

Long-Term Coefficients			
Variable	**Coefficient**	**Std. Error**	**Prob**
ln ACass	−1.1033 ***	0.1963	0.0001
ln Rulpop	1.4183 ***	0.2902	0.0003
ln RPMaiCass	0.1740 *	0.0969	0.0958
ln RPYamCass	0.6350 **	0.2608	0.0301
ln RPBeaCass	−0.4241 **	0.1600	0.0200
ln Exr	0.3574 **	0.1470	0.0303
ln MSavprec	0.2827 **	0.1026	0.0164
ln LSavprec	0.0110	0.0723	0.8819
ln MSavprec _Var	0.0417	0.0448	0.3681
ln LSavprec _Var	−0.1345 *	0.0668	0.0652
ln MSavtemp	2.8315	1.7157	0.1228
ln LSavtemp	−5.4506 **	2.4647	0.0455

NB: significance level *** 1%, ** 5%, * 10%.

Although an increasing availability of labour has no significant effect on cassava yields in the short term, a 10% increase in labour leads to a 14.18% increase in yield in the long term. In the short term, where the area of crop harvested is generally fixed, increasing the availability of labour may induce a 'flower pot' effect (*increasing labour used on a fixed area of land per unit of time may first increase output only up to a point, and decline thereafter; this may result in the observed insignificant short-term effect*), and result in the observed insignificant response. In the long run, where farmers adjust appropriately to changes in the system, an increasing availability of labour becomes highly beneficial to cassava production. This affirms the importance of labour in cassava production in Togo.

In line with previous studies in West Africa (e.g., [28,34]), a significant effect of changing crop prices on cassava production is found in this study. Whereas the yield of cassava increases with an increasing real producer price ratio between the crop and its common intercrops in the country (maize and yam, [26]), it decreases with an increase in the price ratio between common beans (usually sown as a monocrop) and cassava. This indicates that while resource re-allocation by farmers in favour of maize and yam following increments in the relative price ratio may have no adverse effects on cassava yields, a drift of resources towards production of common beans may significantly reduce cassava yields. As a tradable (exportable) commodity (mostly in processed form), a depreciating exchange rate makes exports of this commodity more beneficial for domestic producers and exporters, stimulates domestic demand for exportable cassava products, and incites investment in innovative techniques on cassava fields, thereby enhancing yields. A 10% increase in the nominal exchange rate is associated with 2.79% and 3.57% increases in cassava yield in the short and long term, respectively.

All climate variables, except for total rainfall for the lean season, have a significant effect on the yield of cassava in the short term. In the long term, however, only changes in total rainfall for the main season, variability of rainfall during the lean season and changes in lean-season mean temperature have significant effects on cassava yield. From these, we note that cassava yield is influenced by both 'normal' climate variables (total rainfall and mean temperature) and within-season rainfall variability. The insignificant effect of total lean-season rainfall on cassava yield is in conformity with a study in Nigeria by [55], who found that, after seven months of planting, rainfall appears to have no significant effect on cassava yield. A positive response of cassava yield to increasing volumes of rain and to increasing mean temperature during the main season is observed. The main season in Togo coincides with planting, early and late vegetative stages of the crop. Although increasing temperature is mostly associated with increasing evaporation and transpiration in plants, the high availability of moisture during the main season (due to intense and persistent rain) enables the crop to utilize higher temperatures and moisture to increase the rate of germination, leaf number, leaf formation rate, canopy formation, growth rate and yield [36,56]. A 10% increase in main-season rainfall and mean temperature leads to respective increments of 2.02% and 19.44% in cassava yield in the short term. Yield also increases by 2.83% in the long run, with a 10% increase in main-season rainfall. The insignificant effect of main-season temperature in the long run may be attributed to the cumulative effect of warming during the main season, which neutralizes the short-term benefits derived from increasing main-season temperature. Due to the relatively low rainfall/temperature ratio in the lean season, the yield of cassava is found to be highly sensitive to increasing lean-season mean temperature. Given the low soil moisture and limited water supply (*due to the high reliance of farmers on rain for appreciable yields and the limited use of irrigation in the study area*) during the lean season, increasing temperature during this period leads to severe water and heat stress driven by water deficits, evaporation, and transpiration. This consequently leads to a significant decrease in the yield of cassava in the country. The observed negative effect of increasing lean-season mean temperature on cassava yield is in conformity with findings by [36,57]. In a study by [57], the root initiation and tuberization stages (which coincide with the lean season in the study area) were found to be the critical period for a water-deficit effect in cassava. Similarly, a study in East Africa by [36] found that crops are more precipitation-constrained during the lean season, and increasing evaporation due to increased lean-season mean temperature leads to a significant decrease in output. From Table 3, a 10% increase in lean-season mean temperature leads to 47.80% and 54.51% decreases in cassava yield in the short and long term, respectively. Due to the relatively low water availability/supply during the lean season, increasing within-lean-season rainfall variability induces either drought or flood, both of which have detrimental effects on yield. Investment in innovative techniques like water harvesting (in case of excess rainfall), breeding for drought-, heat- and flood-tolerance, adjustment of cropping calendar and practice of supplemental irrigation (in case of droughts/dry spells) could help minimize the detrimental effect of within-lean-season rainfall variability and increasing lean-season mean temperature.

In summary, this study affirms an inverse farm size and productivity relationship in both the short and long term. In the long run, where farmers can appropriately adjust to changes in the system, an increasing availability of labour becomes beneficial to crop production. Prices do influence cassava yield, but the effects depend on the relative ratios considered. For common intercrops of cassava (maize and yam), increasing real producer price ratios between the crops and cassava has no detrimental effect on cassava yield. An increase in the ratio between the price of common beans and cassava, however, leads to a decrease in cassava yield due to potential resource allocation in favour of common beans (usually sown as a monocrop). A depreciating exchange rate enhances the yield of cassava in Togo. With regards to climate effects, we found main-season rainfall, within-lean-season rainfall variability, and lean-season mean temperature to be the major climatic drivers of cassava yield in Togo. In assessing the efficiency of estimated coefficients and appropriateness of model specification, we find that the residuals are normally distributed, non-serially correlated, and homoscedastic (see Table 4). In addition, the F-statistic for the Ramsey RESET test is not significant, indicating a lack of specification errors. Both the CUSUM and CUSUM of Squares tests affirm stable and reliable coefficients (see Figure 4)

Table 4. Coefficient diagnostics.

Breusch–Godfrey LM	Breusch–Pagan–Godfrey Heteroskedasticity Test	Residual Normality Test	Ramsey RESET Test
F-stat (Prob)	F-stat (Prob)	Jarque–Bera (Prob)	F-statistics (Prob)
0.0401 (0.8447)	1.7293 (0.1639)	1.3972 (0.4973)	1.4922 (0.2453)

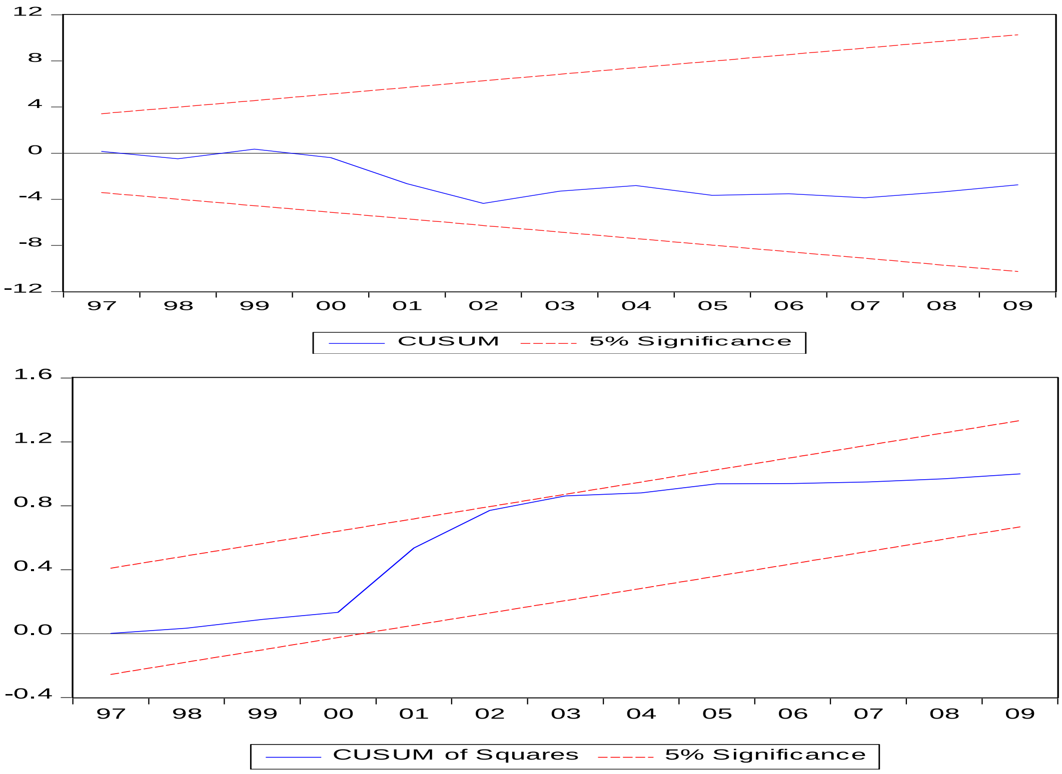

Figure 4. Reliability and stability test of coefficients.

5.3. Causality

In analyzing causation, and as shown in Table 5, a bilateral causality is found between area harvested and yield of cassava. However, four unidirectional causalities are found: from labour availability (rural population), real producer price ratio between yam and cassava, main-season rainfall and lean-season mean temperature to cassava yields. These findings indicate that, whereas the majority of the estimated effects in previous section could be regarded as general correlations, the effects of area harvested, real producer price ratio between yam and cassava, and of dynamics in main-season rainfall and lean-season mean temperature have causal implications for cassava yields in Togo. Measures to couple area expansion with increasing labour availability, increasing water supply during the main season and minimization of heat and water stress during the lean season, could enhance cassava yields in the country.

Table 5. Pairwise Granger causality tests (sample: 1978–2009; Lags 5).

Null Hypothesis	Obs	F-Stat	Prob
lnACass does not Granger Cause lnYCass lnYCass does not Granger Cause lnACass	27	3.74709 3.01806	**0.0195** **0.0417**
ln Rulpop does not Granger Cause lnYCass lnYCass does not Granger Cause ln Rulpop	27	4.4412 2.4099	**0.0100** 0.0824
ln RPMaiCass does not Granger Cause lnYCass lnYCass does not Granger Cause ln RPMaiCass	27	2.31083 0.83260	0.0925 0.5453
ln RPYamCass does not Granger Cause lnYCass lnYCass does not Granger Cause ln RPYamCass	27	3.23633 0.94357	**0.0330** 0.4798

Table 5. *Cont.*

Null Hypothesis	Obs	F-Stat	Prob
ln RPBeaCass does not Granger Cause lnYCass lnYCass does not Granger Cause ln RPBeaCass	27	2.15389 0.76413	0.1112 0.5888
D (ln Exr) does not Granger Cause lnYCass lnYCass does not Granger Cause D (ln Exr)	26	0.06309 1.17795	0.9968 0.3653
ln MSavprec does not Granger Cause lnYCass lnYCass does not Granger Cause ln MSavprec	27	5.46868 1.17301	**0.0040** 0.3649
ln LSavprec does not Granger Cause lnYCass lnYCass does not Granger Cause ln LSavprec	27	0.83759 1.76667	0.5422 0.1768
ln MSavprec _Var does not Granger Cause lnYCass lnYCass does not Granger Cause ln MSavprec _Var	27	2.0656 0.9859	0.1234 0.4565
ln LSavprec _Var does not Granger Cause lnYCass lnYCass does not Granger Cause ln LSavprec _Var	27	0.2441 1.9943	0.9368 0.1344
ln MSavtemp does not Granger Cause lnYCass lnYCass does not Granger Cause ln MSavtemp	27	2.42447 1.86988	0.0810 0.156
ln LSavtemp does not Granger Cause lnYCass lnYCass does not Granger Cause ln LSavtemp	27	3.98566 2.04236	**0.0154** 0.1269

NB: D (ln Exr)—log of exchange rate expressed in first-differenced form to ensure that all variables, used for the test are stationary. Bold—significant at either 5% or 1% level; Source: Output of Pairwise Granger Causality Tests in EViews 9 (SV).

6. Conclusions and Policy Recommendations

From a leading position in cassava productivity during the late 1960s to early 1980s, Togo is now one of the countries with the lowest cassava yields in the West and Central African sub-region. Togo observed a 63.49% decrease in cassava yields between the years 1964 and 2013. Due to the significant role played by the cassava sub-sector in food security enhancement, poverty reduction, agricultural growth and national development, this decreasing trend in yield is deemed worrisome. To inform policy and stakeholder decisions on the measures needed to enhance cassava yields in the country, several research efforts have been made. Emphasis has, however, so far been placed on biotic determinants of cassava productivity, with very little (if any) done to ascertain the effects of climatic, socioeconomic and policy determinants. This study sought to bridge the current knowledge gap in this regard, making use of secondary data on production statistics, rural population, climate variables, prices and nominal exchange rate series for the period 1978–2009. An autoregressive Distributed Lag (ARDL) modelling approach and pairwise Granger Causality tests were used for the analysis.

Besides an inverse farm size and productivity relationship found in this study, results for the short- and long-term models of ARDL indicate that, although the effect of increasing labour availability is not significant in the short term (due to the limited ability of farmers to make appropriate adjustments in the short term), increasing labour availability has a significant positive and elastic effect on cassava yield in the long run. This reveals the importance of labor in cassava production in Togo. This study also found that producer prices do influence cassava yields. The specific effect, however, depends on whether the price change is between cassava and its common intercrops (maize and yam) or between cassava and crops usually sown in monocropping systems (with an emphasis on common beans in this study). Whereas changes in the former are found to be beneficial for cassava production, changes in the latter are found to be detrimental. We found that the yield of cassava is influenced by both 'normal' climate variables (total rainfall and mean temperature) and within-season variability in rainfall. In both the short and long term, however, the effect of total lean-season rainfall was not significant. In contrast, the effect of within-lean-season rainfall variability was found to be significant in both the short and long term. Given the relatively low water availability/supply during the lean season, high within-lean-season rainfall variability could lead to drought (dry spell) or flooding, both of which could have detrimental effects on yield. In addition to these, we found a highly elastic response of cassava yields to increasing lean-season mean temperature. This elastic response is attributed in part to the low rainfall/temperature ratio in the lean season and to severe water and heat stress driven by water deficits, evaporation, and transpiration with increasing lean-season mean temperature. A 10% increase in lean-season mean temperature is associated with 47.80% and 54.51% decreases in cassava yield in the short and long term, respectively. Investment in innovative techniques like water harvesting, breeding for drought, heat and flood tolerance, adjustment of cropping calendar and practice of supplemental irrigation could help minimize the detrimental effects of within-lean-season rainfall variability and increasing lean-season mean temperature. Although increasing temperature is generally associated with increasing evaporation and transpiration in plants, we found that a high availability of moisture during the main season (due to intense and persistent rain) enables the crop to utilize higher temperatures and moisture during the main season to increase yields. Through pairwise Granger Causality tests, we found a bilateral causality between area harvested and yield of cassava, and four unidirectional causalities from labour availability, real producer price ratio between yam and cassava, main-season rainfall and lean-season mean temperature to cassava yields. Whereas the majority of the estimated effects in this study could be regarded as general correlations, the effects of area harvested, real producer price ratio between yam and cassava, main-season rainfall and lean-season mean temperature have causal implications for cassava yields. To increase the productivity of cassava in Togo, efforts should be made to increase the water supply during the main season and minimize water and heat stress during the lean season. This could be achieved through investment in low-cost irrigation facilities to enhance the practice of supplemental irrigation, water harvesting, and breeding for drought, heat and flood tolerance. In addition, efforts should be made to couple area expansion with increasing availability of labour, through implementation of measures to minimize rural–urban migration (to ensure the ready availability of labor in the cassava-producing areas).

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Conflicts of Interest: The author declares no conflict of interest.

Appendix A

Appendix A.1. Sections

Appendix A.1.1. Section AE 1

Per research on Bounds testing approaches by [44], an ARDL model for a dependent variable Y, a set of independent variables X, and a vector of deterministic variables E (if any) (e.g., time trends, seasonal dummies, or exogenous variables with fixed lags) can be written as follows [46]:

$$\theta(L,P)Y_t = \propto_0 + \sum_{i=1}^{k} \beta_i(L,q_i)X_{i,t} + \varphi' E_t + \mu_t \ , \tag{A1}$$

where

$$\theta(L,P) = 1 - \theta_1\varphi_1 L^1 - \theta_2\varphi_2 L^2 - \ldots - \theta_p L^p \tag{A2}$$

$$\beta_1(L,P_1) = \beta_{i0} + \beta_{i1}L^1 + \beta_{i2}L^2 + \ldots + \beta_{iqi}L^{qi}, \ i = 1,2,\ldots,k \ , \tag{A3}$$

where $\propto_0$ represents the intercept, and L is a lag operator.

In the long term,

$$Y_t = Y_{t-1} = Y_{t-2} = \ldots = Y_{t-p} \ ; \ X_{i,t-1} = X_{i,t-2} = \ldots = X_{i,tq} \ , \tag{A4}$$

where $X_{i,tq}$ represents the qth lag of the ith independent variable.

From Equation (A1), the long-term response of Y_t to a unit change in $X_{i,t}$ is estimated as follows:

$$\beta_i = \frac{\hat{\beta}_i(l, \hat{q}_i)}{\theta(l, \hat{p})} = \frac{\hat{\beta}_{i0} + \hat{\beta}_{i1} + \ldots + \hat{\beta}_{i\hat{q}}}{1 - \hat{\theta}_1 - \hat{\theta}_2 - \ldots - \hat{\theta}_{\hat{p}}},\ i = 1,\ 2,\ \ldots,\ k. \tag{A5}$$

From Equation (A5), $\hat{q}_i$ and $\hat{p}$ are the estimated values of p and q_i.

Following a confirmation of long-term relationships by the Bounds test, Equation (A1) is re-parameterized to produce the following error correction representation of the ARDL:

$$\Delta Y_t = \gamma_0 - \sum_{j=1}^{\hat{p}-1} \theta_j \Delta Y_{t-j} + \sum_{i=1}^{k} \beta_{i0} \Delta X_{it} - \sum_{i=1}^{k} \sum_{j=1}^{\hat{q}_{t-1}} \beta_{ij} \Delta X_{i,t-j} + \varphi' \Delta E_t \ - \ \theta\left(1, \hat{P}\right) ECM_{t-1} + \mu_t \tag{A6}$$

and

$$ECM_t = Y_t - \hat{\propto} - \textstyle\sum_{i=1}^{k} \hat{\beta}_i X_{it} - \varphi' E_t\ , \tag{A7}$$

where Δ represents first difference operator, $\boldsymbol{\theta_j}$, $\boldsymbol{\beta_{ij}}$, and $\boldsymbol{\varphi'}$ are estimated coefficients for the short-term (error correction) model, $\boldsymbol{\gamma_0}$ represents the short-term intercept and $\boldsymbol{\theta}\left(\mathbf{1}, \hat{\boldsymbol{P}}\right)$ the coefficient for the error correction term. This latter value reflects the speed at which deviations from long-term equilibrium for the systems are corrected for in the short term.

Appendix A.1.2. Section AE 2

As defined by [48,49], causality is based on two basic principles:

(i) The cause happens prior to its effects and
(ii) The cause has unique information about the future values of its effect.

In line with these two basic principles, [48] proposed testing the following hypothesis for identification of causality:

$$P[Y(t+1) \in A | Ж(t)] \neq P[Y(t+1) \in A | Ж_{-x}(t)]\ , \tag{A8}$$

where A represents an arbitrary non-empty set, while the symbols $Ж(t)$ and $Ж_{-x}(t)$ denote complete information until time t in the entire universe and the modified universe in which X is excluded, respectively. In instances where the above hypothesis is accepted, X is said to Granger cause Y. Specification of the appropriate equations for establishing such causalities depends on the order of integration of the variables. Given two stationary variables X and Y, and lag order 'N', Granger causality can be assessed directly through the following regressions involving lagged values of each of the variables and their originals:

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \ldots + \beta_j Y_{t-j} + \propto_1 X_{t-1} + \ldots + \propto_j X_{t-j} + u_t \tag{A9}$$

$$X_t = \gamma_0 + \gamma_1 X_{t-1} + \ldots + \gamma_j X_{t-j} + \delta_1 Y_{t-1} + \ldots + \delta_j Y_{t-j} + v_t \tag{A10}$$

where u_t and v_t are the error terms and are assumed to be uncorrelated. In the above specifications, emphasis is placed on testing the following hypotheses:

1. Null: X_t does not Granger cause Y_t

   $H_0 : \propto_1 = \propto_2 = \ldots = \propto_j = 0$

   $H_1 : \propto_1 = \propto_2 = \ldots = \propto_j \neq 0$

2. Null: Y_t does not Granger cause X_t

   $H_0 : \delta_1 = \delta_2 = \ldots = \delta_j = 0$

   $H_1 : \delta_1 = \delta_2 = \ldots = \delta_j \neq 0$

Should H_0 be rejected in either or both cases, Granger ('predictive') causality is said to exist between the variable. A rejection or non-rejection of the null hypothesis could lead to four possible outcomes:

(i) A unidirectional Granger causality from X_t to Y_t (when H_0 is rejected in the first case);
(ii) A unidirectional Granger causality from Y_t to X_t (when H_0 is rejected in the second case);
(iii) Feedback, or bilateral causality (when H_0 is rejected in both cases);
(iv) No causality (when we fail to reject H_0 in both cases).

Appendix A.2. Tables

Table A1. Cassava production, acreage and yield statistics for Togo.

Variable	Period	Year Min Max	Min	Max	Mean	Std. Dev	CoV, %	Annual Growth, %
Output (tons)	1964–1973	1964 1969–71	380,000	500,000	442,034.9	46,723.4	10.57	1.31
	1974–1983	1977 1979	319,060	432,535	383,191.7	34,922.9	9.11	−1.09
	1984–1993	1987 1990	355,200	592,867	445,134	68,100.1	15.3	0.66
	1994–2003	1994 2003	531,526	778,865	643,736.1	83,117.5	12.91	4.02 ***
	2004–2013	2004 2011	675,475	998,540	835,525.9	113,564.1	13.59	4.31 ***
	1964–2013	1977 2011	319, 060	998,540	549,924.5	183,975.9	33.45	1.80 ***
Area (Ha)	1964–1973	1973 1971	21,000	33,000	26,700.00	4,056.5	15.19	−0.52
	1974–1983	1976 1982	20,630	108,700	43,980.00	32,923.0	74.86	21.05 ***
	1984–1993	1987 1984	45,104	79,600	62,461.10	10,270.2	16.44	−0.19
	1994–2003	1994 2003	90,403	132,943	108,771.2	15,246.7	14.02	4.10 ***
	2004–2013	2005 2012	113,470	155,000	136,691.1	14,565.7	10.66	3.26 ***
	1964–2013	1976 2012	20,630	155,000	75, 720.68	44,906.9	59.31	4.51 ***
Yield (tons/ha)	1964–1973	1971 1973	15.15	20.35	16.71	1.54	9.24	1.84 *
	1974–1983	1982 1974	3.38	19.63	12.61	6.36	50.47	−18.29 ***
	1984–1993	1984 1987	5.58	7.88	7.18	0.69	9.62	0.85
	1994–2003	2000 1997	5.65	6.23	5.93	0.21	3.61	−0.08
	2004–2013	2006 2011	5.62	6.56	6.10	0.25	4.17	1.02 **
	1964–2013	1982 1973	3.38	20.35	9.70	5.16	33.45	−2.60 ***

NB: *** 1%, ** 5%, * 10%. Source: Author's own computation with data from FAOSTAT.

Table A2. Distribution of major crops/livestock by region.

Regions	Population in 2010	Area (km^2)	Main Crops/Livestock
Coastal zone/Maritime	2,599,955	6100	Corn, cassava, cotton, oil palm, peri-urban livestock farming (poultry, pigs) market gardening
Western/Plateaux forest	1,375,165	16,975	Diversified farming: coffee, cocoa, oil palm to the southeast (Kpalimé), corn, cassava, yams, lowland rice, fruits, small ruminants, traditional poultry
Eastern Plateaux			Cotton, corn, black-eyed peas, peanuts, lowland rice, cattle, small ruminants, traditional poultry
Centrale	617,871	13,317	Cotton, corn, sorghum, millet, rice, cassava, yams, black-eyed peas, peanuts, soya, cattle, small ruminants, traditional poultry
Kara	769,940	11,738	Cotton, corn, sorghum, yams, tomatoes, rice, black-eyed peas, soya, peanuts, cassava, millet, cattle, sheep, goats, traditional poultry, bees, etc.
Savanes	828,224	8470	Cotton, sorghum, millet, rice, yams, peanuts, black-eyed peas, cattle, small ruminants, traditional poultry

Source: Government of Togo and United Nations [21] and Wikipedia. (*https://en.wikipedia.org/wiki/Regions_of_Togo*).

Table A3. Estimation equation (base model). Selected ARDL (3,0,0,0,0,0,0,0,0,0,0,0,0,0); Maximum dependent lags:3 (Automatic selection); Model selection method: Schwarz criterion (SIC); Trend specification: Unrestricted intercept; Included Observations: 29 after adjustments.

	Coefficient	Std. Error	Prob.
ln YCass (−1)	0.2521 **	0.0906	0.0155
ln YCass (−2)	−0.2572 **	0.1030	0.0267
ln YCass (−3)	0.1551 **	0.0584	0.0197
ln ACass	−0.9377 ***	0.0972	0.0000
ln Rulpop	1.2054 ***	0.1817	0.0000
ln RPMaiCass	0.1479 *	0.0793	0.0849
ln RPYamCass	0.5397 **	0.1877	0.0130
ln RPBeaCass	−0.3604 ***	0.1156	0.0082
ln Exr	0.3038 ***	0.0985	0.0087
ln MSavprec	0.2403 ***	0.0763	0.0077
ln LSavprec	0.0093	0.0609	0.8808
ln MSavprec _Var	0.0355	0.0400	0.3913
ln LSavprec _Var	−0.1143 **	0.0518	0.0458
ln MSavtemp	2.4065 *	1.3262	0.0927
ln LSavtemp	−4.6325 **	1.8269	0.0249
Intercept	6.7240	5.3919	0.2344
Adj. R-squared	0.9146	Log likelihood	52.565
F-statistic	20.993	Akaike info criterion	−2.522
Prob (F-statistic)	0.0000	Schwarz criterion	−1.767
Durbin-Watson	2.0046	Hannan–Quinn criter.	−2.285

NB: *** 1%, ** 5%, * 10%. Source: Output of EViews 9 (SV).

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