Adapting to climate change in the rainfed farming systems in Eastern Africa: a support vector machine analysis

Jean Luc Mubenga-Tshitaka, Dambala Gelo Kutela, and Johane Dikgang[1]

Abstract

We estimate the production function for agriculture output in Eastern Africa by incorporating climate variables. We disaggregate these variables into growing and non-growing seasons and we use an asymmetric generalized autoregressive conditional heteroscedasticity (GJRGARCH) to capture the time-varying aspect of the variability in the temperature and rainfall. The asymmetric variability model has the advantage of capturing extreme values. Data were collected from the food and agriculture organization (FAO), spanning from 1961 to 2017. We find that within spring growing variability has a significant impact on crop production. Utilizing all the independent variables, a support vector machine (SVM) was implemented and compared to the baseline production function for agriculture output. The results reveal that SVM has outperformed the baseline model in terms of root mean squared error and mean absolute error to forecast agricultural output. Our results reveal that labor, land, livestock and spring variability in precipitation are the most important factors that affect agricultural output. Policy implications are discussed.

Keywords: adaptation, climate change, Eastern Africa, GJR-GACH, support vector machine.

[1] Public and Environmental Economics Research Centre (PEERC), School of Economics, University of Johannesburg, Johannesburg, South Africa. Email: jeanlucmubenga@yahoo.fr.

1. Introduction

Unlike in other regions in the world, Eastern Africa continent depends on the agriculture rain-fed and dominated by small scale production. Eastern Africa like other parts of Africa depends on agricultural production (World Bank, 2007). This dependency is mainly threatened by the importance of the within growing season precipitation variability documented in the Eastern Africa literature (Schreck and Semazzi, 2004, Conway *et al*, 2005, You *et al*, 2009 Conway and Schipper, 2011, Bahaga *et al*, 2014). This within growing precipitation might have a positive impact on outputs based on the type crop and the agro-ecological area (Thornton *et al*, 2006). The majority of crops produced in this region are rainfed, implying any variability in the growing season will impact negatively the overall agricultural production. Hence, the livelihoods in rural Eastern Africa depend on rainfed agriculture products (Bowden and Semazzi, 2007). Agriculture in this region is organized by smallholder contribution up to 90% of the total production which represents up to 40% of the national gross domestic product (Adhikari et al, 2015).

Climate variability in Eastern Africa is the results of complex topography, latitudinal location, and effects from regional and global atmospheric circulation (Bowden and Semazzi, 2007). Rainfall and temperature variability are two most important climate variables that impact on human livelihoods, ecosystems and socioeconomic characteristics (Omondi et al, 2014). The importance of within growing season variability of temperature and precipitation in crucial for policy design as its impact can be easily corrected by small technology (Kahsay and Hansen, 2016).

Barrios et al, (2008), Rowhani *et al*, (2011), Ward *et al*, (2014) and Kahsay and Hansen (2016) used the coefficient of variation as a measure of climate variability for precipitation and temperature (Rowhani et al, 2011). The variance measurement assumes that data follow a normal distribution pattern. While there is some consensus that climate change produces extremes temperature and rainfall (Conway and Shipper, 2011, Tong *et al*, 2019) and in Eastern Africa (Ongoma and Chen, 2017) that seems not to be captured by the normal distribution assumption. This study will differ from others for various reasons. Firstly, contrary to Tol (1996) who proposed a generalized autoregressive conditional heteroscedastic (GARCH) to model the conditional variance of the temperature that depends linearly on the conditional variances of previous temperatures and prediction errors. Franses *et al* (2001) used quadratic GARCH, Romilly (2005) used GARCH

In this paper, we introduce the GJR-GARCH model to capture the asymmetric behavior of the climate variable. Secondly, this paper proposes the SVM as a tool to improve accuracy in the prediction of agriculture outputs. Prediction or climate prediction has the potential to reduce the effect of weather or other changes observed in agriculture outputs. If an anomalous pattern can be detected in advance by taking into account of the drivers of the change observed in the agriculture outputs. Farmers and policymakers will be more effective in their practices and policy implementation. This might enhance food security.

Our results reveal that GJR-GARCH captures well the asymmetric pattern observed within growing temperature and precipitation. In addition, the SVM provides more accurate results and labor, land, livestock, and spring within growing season temperature remain the most contributing factors in the variability observed in agriculture output.

The remaining of this paper is organized as follows, Section 2 deals with agricultural production and climate variability. Section 3 provides a brief summary of the techniques used in this study. While Section 4 and 5 present the sources of data and the results of this study. Section 6 concludes this paper

. Climate variability and agriculture production in East Africa

Eastern Africa, also called the Greater Horn of Africa, is presented as a major dry climate anomaly region, covering eleven countries which are Burundi, Djibouti, Ethiopia, Eritrea, Kenya, Somalia, South Sudan, Sudan, Rwanda, Tanzania, and Uganda. Eastern Africa is relatively a dry land and situated between 12 ° S and 12 ° N despite the fact of being close to the equatorial region (Yang *et al*, 2015).

East Africa's economy is highly depending on agriculture, 40% of the gross domestic product and provides the main income up to 80% (Runge at el, 2004), leading to strong vulnerability of communities to any fluctuations in seasonal rainfall amounts. Hence, the knowledge regarding the evolution of the seasonal rainfall and temperature under future climate conditions is crucial for risk management purposes. Studies provide sufficient evidence of within seasonal variabilities in climate variables in East Africa (Nicholson and K, 1997, Schreck and Semazzi, 2004, Conway *et al*, 2005.; Anyah and Semazzi, 2007). While agriculture in the region is dominated by small-farming practices, with low inputs in physical capital, fertilizer pesticides

(Erissen *et al*, 2008), depending on rainfed agriculture system accounting for up to 95% of the land used for cultivation (Slingo, *et al*, 2009).

2. Model Specification

2.1 Baseline model

We will use the standard production function that is regressed with the agriculture output on inputs and expresses as follows:

$$Q = F(L, K, \mathrm{I}) \tag{1}$$

where Q stands for agriculture output, L is labor, K for capital like land, machinery, and livestock, I refers to other factors like fertilizer and irrigation. We use also assume a Cobb-Douglas model like in Kahsay and Hansen (2016) but we will depart by them by not including the country-specific time trend. This model will be used as a baseline model for comparison purposes.

$$Q = L^{\beta_1} K^{\beta_2} \mathrm{I}^{\beta_3} \tag{2}$$

In the long-form, we can express it as follows:

$$\ln(Output_{it}) = \beta_0 + \beta_1 \ln(Labor_{it}) + \beta_2 \ln(Land_{it}) + \beta_3 \ln(Machinery_{it}) + \beta_4 \ln(Livestock_{it}) + \beta_5 \ln(Fertilizer_{it}) + \beta_6 ln(Irrigation_{it}) + \sum_{n=1}^{3} \alpha_{1s} \ln(Temp_{ist}) + \sum_{n=1}^{3} \alpha_{2s} \ln(Precip_{ist}) + \sum_{n=1}^{3} \lambda_{1s} \ln(Variability_{ist}^{Temp}) + \sum_{n=1}^{3} \lambda_{2s} \ln(Variability_{ist}^{Precip}) + \mu_t + \varepsilon_{it} \tag{3}$$

where $Output_{it}$ is the total agriculture production of country *i* in year *t*. We include three capital inputs: Land, Machinery, and Livestock. We also include one aggregate Labor, Fertilizer Irrigation, μ_t is unobserved time-invariant country-specific and ε_{it} errors term. We follow Barrios et al (2008), Molua (2008) and Kahsay and Hansen (2016) to specify the agriculture production functions. $Temp_{ist}$ and $Precip_{ist}$ are the mean temperature for the country *i* in season *s* in year *t*. Likewise, $Variability_{ist}^{Temp}$ and $Variability_{ist}^{Precip}$ are within growing season temperature and precipitation variability and we disaggregate them like Barrio et al (2008) and Kahsay and Hansen (2016). Contrary to these two authors, we use the time-varying variability. Autoregressive Conditional Heteroskedasticity (ARCH) and the Generalized ARCH (GARCH) have been used to capture volatility (Engel, 1982 and Bollerslev, 1986). However, studies reveal that ARCH and GARCH models fail to capture the asymmetric features observed in variables and tried to develop a model that captures the asymmetric behavior (see for instance Pagan and Schwert, 1990; Ding *et al*, 1993, Engle and Ng, 1993, Hentschel, 1995). Variability is not only time-varying but also the future variability is related to past innovations that found in the extreme's values of the distribution. Glosten Jagarnnathan and Runkle (1993) add an additional term in the conditional variance to make the GJR-GARCH approach. The expression for the variance can be defined as follows:

$$\sigma_i^2 = \tau_0 + \sum_j^q \beta_i \sigma_{j-q}^2 + \sum_{j=1}^p \alpha_{1i}\, \varepsilon_{t-p}^2 + \alpha_2 S_{t-1}^- \varepsilon_{t-1}^2 \quad (4)$$

where $S_{t-1}^- = 1$ if $\varepsilon_{t-1} < 0$ and $S_{t-1}^- = 0$ if $\varepsilon_{t-1} \geq 0$. The proposed model is denoted as GJR-GARCH. Equation (4) is subjected to

$$p \geq 0\ ,\ q \geq 0, \tau_0 > 0, \alpha_i > 0,\ i = 1,2,3 \cdots p, \beta_i > 0, j = 1,2,3 \cdots q \quad (5)$$

2.2 Support vector machine

Support vector machine (SVM) is one of the machine learning techniques for classification and regression developed by Vapnik et al (1995). The basic idea of SVM lies into transforming the input space into a high-dimensional feature space through nonlinear transformation and extract the information and regularity contained amongst the data. Hence the nonlinear relationship between the input and output variables is found in the-dimensional space. The SVR differentiates itself from other methods through achieving a high degree of consistency by relying upon only a subset of the training observations known as the support vectors (Jain, 2014). Given a set of data trained $(x_1, y_1) \dots (x_m, y_m)$, $(x_i \in X = R^n, y_i \in Y = R,$ m is the number of training samples) are randomly and independently regenerated from an unknown function. SVM approximates the regression function as follows:

$$f(x) = \omega.\phi(x) + b \quad (6)$$

where x is the input parameter, $\phi(x)$ is the high dimensional feature space that is mapped nonlinearly from the input space $x; \omega$ is the weight coefficient; and finally, b represents the deviation parameter. The coefficients of ω and b are calculated through minimization of the regularized risk function:

$$\frac{1}{2} \parallel \omega \parallel^2 + C \frac{1}{n} \sum_{i=1}^n L_\varepsilon(y_i, f(x_i)) \quad (7)$$

where $\parallel \omega \parallel^2$ represents a regularized term; minimizing the regularised term can make a function as flat as possible. C is the regularized constant term and ε represents the threshold of the support vector machine. The term $1/n \sum_{i=1}^n L_\varepsilon(y_i, f(x_i))$ is the empirical error measured by the ε-insensitive loss function, expressed as:

$$L_\varepsilon\big(y_i, f(x_i)\big) = \begin{cases} |y_i - f(x_i)| - \varepsilon, |y_i - f(x_i)| \geq \varepsilon \\ elsewhere \end{cases} \quad (8)$$

Equation 3 shows the ε −Support Vector Regression (ε −SVM). If the predicted value is within the tube, the loss value is zero. However, if the predicted value is outside the tube, the loss value is the magnitude of the difference between the predicted value and radius ε of the tube. To obtain the estimation of ω and b, Equation (1) is transformed into the primal objective function named (4) by introducing the positive slack variables ξ_i^*.

$$min \frac{1}{2} \parallel \omega \parallel^2 + C\frac{1}{n}\sum_{i=1}^{n}(\xi_i + \xi_i^*) \quad (9)$$

To solve the optimization problem, Lagrange multipliers like α_i and a_i^* are introduced in order to partially derived to the primal variables, the problem of equation (4) can be resolved in its duals formulation as follows:

$$Max\omega(a_i, a_i^*) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)y_i - \frac{1}{2}\sum_{i,j=1}^{n}(\alpha_i - \alpha_i^*)\big(\alpha_j - \alpha_j^*\big)\langle\phi(x_i).\phi(x)\rangle - \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)\varepsilon \quad (10)$$

Finally, the solution to Equation (1) can be obtained as follows:

$$f(x) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)\ \phi(x_i).\phi(x) + b \quad (11)$$

After introducing the Kernel function $K\big(x_i, x_j\big)$, Equation (1) can be rewritten as

$$f(x) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*).K(x_i, x) + b \quad (12)$$

where x_i is the input vector of prediction year; $f(x)$ is the set of the output vector. The selection of the kernel function is crucial to the accuracy of the final prediction model. Due to less numerical difficulties and nonlinear property in a high dimensional space, radial basis function (RBF) is chosen as the kernel function, which is represented by Equation (13)

$$K(x_i, x) = exp\{-g \parallel x_i - x_j \parallel^2\} \quad (13)$$

where x_j is the input vector of the training years, g is the kernel parameter. Generally, parameters c and g are important factors that directly impact the accuracy of the prediction model.

The accuracy of the baseline model versus SVM, was assessed with multiple statistical score metrics (i.e. coefficient of determination, R^2; mean absolute error (MAE) and mean squared error (MSE) (see for example Chai and Draxler, 2014). The MAE seems to be the most natural one, since it is simply the average of all found errors, via their absolute values in order to avoid error offset. While the RMSE does the same thing and squared the errors to avoid error offset. The MSE and MAE are defined by

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(P_i - O_i)^2} \quad (14)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|P_i - O_i| \; , \quad (15)$$

respectively, where P_i is the predicted variable and O_i is the observe variable. These criteria are the amount the most common error measurements reported in the literature.

3. Data description

Data from 9 countries (Burundi, Djibouti, Ethiopia, Kenya, Rwanda, Somalia, Sudan, Tanzania, and Uganda) from 1961 up to 2016 were available for this study. These nine countries were considered as in Kahsay and Hansen (2016) due to the similar crop production season characteristics. The period represents 55 years, mainly due to the data availability and a moving average method was considered to fill the missing data. FAOSTAT has been used as our main source of data (FAO, 2011). The FAO' net production index has been used as a dependent variable. This was considered as a proxy of the total production dependent variable and includes both crop and livestock production and other agriculture output. Land inputs are proxied by the total area used for agriculture purposes while machinery input is a proxied by the total number of tractors used. For livestock capital input, we use the number of headcount cattle, sheep and goats. Labor is proxied by the population that is active in the agriculture sector. Fertilizer input is the metric tonnes of plant nutrients consumed in the agriculture sector while the irrigation input is the agriculture area under irrigation.

We also follow Barrios et al (2008), Ward et al (2014) and Abraha Kahsay and Hansen (2016) in the treatment of irrigation interpreted as the quality of land input. We use the Climate Research Unit (CRU) as the main source of climate data like in Barrios *et al* (2008) and Kahsay and Hansen (2016). Like Kahsay and Hansen (2016), $Temp_{Springs}$, $Temp_{Summer}$,$Temp_{Fall}$, $Precip_{Spring}$, $Precip_{Summer}$ and $Precip_{Fall}$ represent the mean temperature and precipitation during spring, summer and fall seasons respectively. While $Variability_{Springs}^{Temp}$, $Variability_{Summer}^{Temp}$, $Variability_{Fall}^{Temp}$, $Variability_{Spring}^{Precip}$, $Variability_{Summer}^{Precip}$ and $Variability_{Fall}^{Precip}$ represent the within growing temperature and precipitation during springs, summer and fall season respectively.

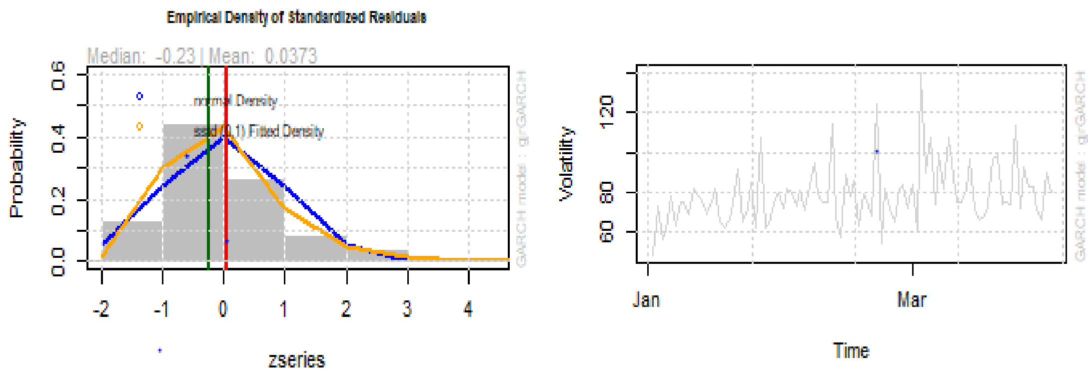
Contrary to Kahsay and Hansen (20016), Cabas *et al.*, (2010) and Rowhani *et al.*, (2011), we use GJR-GARCH, a time-varying variability model to capture the asymmetric behavior observed in climate variability. Tol (1996) reported that large (small) absolute deviations from the mean tend to be cluster while Franses and van Dijk (2001) added that the impact of higher temperature than the expected conditional volatility differs from the impact of temperature lower than expected.

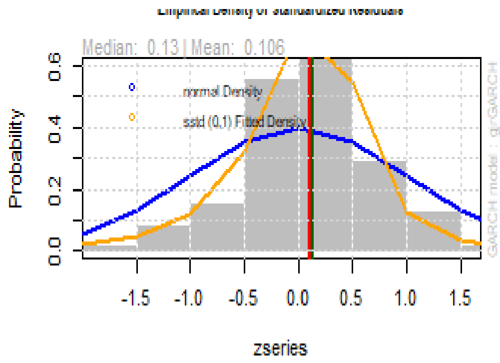
4. Empirical results

Figure1 reports the time-varying variability trends of within-season precipitation and temperature observed in Eastern Africa. We notice that the within growing season precipitation in this region has a distribution that skews toward the right. Meaning there is probability to experience extreme event or change at some point in the time. In addition, the skew distribution implies a higher frequency of the occupancy of the within growing season precipitation. This will have a negative impact on crop production. Hence, the GJR-GARCH volatility model exhibits a better ability to capture the asymmetric effect of the conditional heteroskedasticity that cannot be captured by the coefficient of variation.

The fact of underestimating the magnitude of within growing season and the frequency of their occurrence can lead to wrong policy design. While the with growing season temperature (part 2 of figure 1) is relatively stable and distributed normally but the conditional deviation from the mean tends to cluster, meaning a period of high within growing season temperature tends to be followed by a period of high within growing season temperature (Franses and van Dijk, 2001). The within growing season precipitation tends to present more variability.

Figure 1





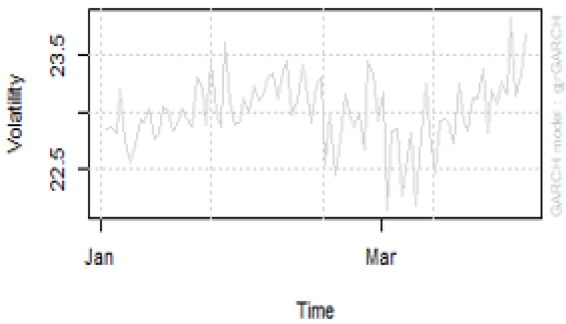


Table 1 reports the estimates of different asymmetric GARCH models considered in this paper. The first of part this table displays the mean outputs that seem to follow an autoregressive with two lags. We calibrate the average temperature of the East Africa region. It turns out that the

Table1 Parameters estimates of GARCH models

	Models		
Parameters	GJR-GARCH (2,0)	IGARCH (2,0)	sGARCH (2,0)
Autoregressive part			
μ_0	73,488564	74,233577	74,291240
	(-0,17814)	(-1,29749)	(-1,24952)
μ_1	-0,116180	-0,130557	-0,129120
	(0,00032)	(0,11941)	(0,11026)
μ_2	-0,113054	-0,152171	-0,159650
	(0,00028)	(0,03722)	(0,10448)
GARCH part			
τ	13,26663	0,001535	30,765170
	(0,03203)	(5,29206)	(15,20198)
α	0,000409	0,000002	0,000010
	(0,00003)	(0,09307)	(0,07269)
β	0,999949	1,000000	0,724590
	(0,00223)	(7,12536)	(0,20795)
s	-0,283118		
	(0,00086)		
skew	1,042554	1,095735	1,150950
	0,184032	0,237018	0,231709
shape	6,793396	3,947101	5,412520
	5,449083	1,868087	3,647764
Akaike	7,783600	8,007400	8,041700
Bayes	8,144900	8,288500	8,362800
Shibata	7,720000	7,967200	7,990300
Hannan-Quinn	7,918300	8,112200	8,161400

IGARCH and SGARCH stand for the integrated GARCH and skew GARCH respectively the average quantity of rain tends to decrease over time. As an alternative way to evaluate the three volatility models considered here and to compare their ability to describe the features in climate variable, we consider the information criteria. Four information criteria were used and we conclude that the GJR-GARCH is more appropriate to capture the volatility in the temperature and rainfall. The coefficient capturing the asymmetric behavior is negative (0,283118) and significant, this opposes to our expectation. Hence, we did not find statistical evidence of the leverage effect in temperature and precipitation in East Africa but there is evidence of asymmetric behavior.

Table 2 lists the basic statistic of the within the growing season for temperature and precipitation. The mean value on spring tends to be higher than in the other periods but associated with higher standard deviation, this makes crops that are mainly rainfed in this region to be more vulnerable. The temperature seems to be stable, in line with the histogram but associated with some degree of variability.

Table 2: Descriptive statistics

	Precipitation		Temperature	
	Mean	St-Dev	Mean	St-Dev
Spring	74,855	13,710	23,018	0,236
Summer	62,184	10,503	23,125	0,261
Fall	64,927	7,198	23,929	0,169

We estimate the Model (3) and consider it as our baseline model. Table 3 reports the results of all performance criteria considered in the study. Forecasting means predicting the level of output production based on inputs and exogenous factors. Exogenous factors are inputs that are external to the control of the producer but have a significant impact on the production. Our sample has 55 years of data points and divided into two subsamples. One is used as a training sample spanning from 1961 to 2010 while the testing period covers the remaining period. The evaluation criteria considered in this study are MAE, RMSE, and R-squared. The results show that SVM provides more accuracy than the linear baseline more. One of the reasons being the assumption of linearity. The baseline model, even though documented significantly in the literature due to easy interpretation, does not capture the full reality of extreme events like drought or flooding in the estimation. RMSE and MAE across countries are small under the SVM model compared to the baseline model. The values of RMSE and MAE are in the range of 0.147-2.372 and 0.136-1.24 respectively for the baseline model and 0.107-0.377 and 0.086-

0.275 respectively for SVM. The baseline model exhibits a higher R-squared coefficient for almost all countries but with most coefficient not statistically significant.

The SVM suggests that labor, land, livestock, and spring within growing season variability are the most contributing factors the changes observed in the output production in Eastern Africa.

Table 3 Forecast evaluation criteria

	BLM			SVM		
	RMSE	R^2	MAE	RMSE	R^2	MAE
Burundi	0.147	0.827	0.136	0.139	0.531	0.115
Djibouti	0.371	0.956	0.368	0.349	0.720	0.275
Ethiopia	0.170	0.985	0.166	0.113	0.929	0.089
Kenya	0.420	0.646	0.400	0.377	0.767	0.186
Rwanda	0.348	0.976	0.350	0.322	0.690	0.225
Somalia	0.234	0.928	0.220	0.107	0.819	0.086
Sudan	2.372	0.490	1.240	0.155	0.396	0.124
Tanzania	0.700	0.961	0.670	0.377	0.767	0.186
Uganda	0.491	0.757	0.430	0.238	0.535	0.189

Labour is the most important factor, this is in line with existing literature since the majority of agriculture activity is held in a rural area. Policymakers should come up with instruments that intend to improve the productivity of farmers, like training. This is following by land accessibility, ownership or degradation. For instance, Ling and Schaab (2010) revealed that the major forest decrease in Easter Africa. Any training taking into account the level of degradation might improve the livelihood of farmers. Livestock is still an important contributor in the agriculture sector in East Africa. Finally, the within growing season variability tends to put pressure on the agriculture products. Besides these variables, others are also important but not as important are these. The policy design should consider the hierarchy in order to design a policy that might improve the welfare of households that depends totally on the agriculture sector.

5. Conclusion

In this paper, we investigated the prediction of agriculture output based on different inputs and how it might help to design a policy that considers variables that contribute the most. Our main contributions are to incorporate a time-varying disaggregate climate variables for the growing and non-growing seasons to cater for the asymmetric behavior observed in the climate variables. We also contribute by using the SVM model as a tool to improve prediction in the agriculture sector. We find the GJR-GARCH account better the within growing season variability than the coefficient of variation. Results reveal also that SVM predicts better the expected agriculture output that the linear model. SVM model emphasis that labor, land, livestock and the spring within growing variability in temperature are the most keys drivers of the agriculture sector. Policymakers should consider the importance of the contribution of each variable for a more effective policy.

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