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ARTICLE

Impact of Climate Change on Food Yield in Senegal: FAVAR Approach

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ABSTRACT

The main objective of this research is to evaluate the impact of climate change on food crop yields in Senegal using the Factor Augmented Vector Auto Regression (FAVAR) approach. The estimation method used is principal components analysis. We identified two major shocks representative of climate change. The first is an increase of temperature (thermal shock) and the second is a decrease in the quantity of precipitation (rainfall shock). The data covers the period 1970-2014 and each of the shocks is carried out over the prior year. The impact of each shock is observed along a time horizon of 10 years. The results show a positive impact of the thermal shock on the yields of rice, maize and millet, with a much greater impact on rice and maize yield. Rising temperatures are, however, detrimental to sorghum. A decline in rainfall has a negative impact on the yields of all cereals, which is in line with expectations.

1. Introduction

Agriculture, mainly subsistence, has for many years been a predominant sector of the Senegalese economy. Subsistence farming is a long-lived practice that has been interfered with by farming over the years. Agriculture plays an important role for a population that grows quickly than its economy and offers a variety of food like millet, sorghum, maize, bean and rice. Food crops cover a wide area of 1 226 823 hectares[1] , i.e., half of the area exploited. Fifty percent of the working population of Senegal is engaged in agricultural activities whose contribution to domestic production is worth 14%[1]. The rural population accounts for 55% of the entire population and collects most of its income from agriculture practices that remain the most dominant activity of the primary sector (more than half of the primary sector GDP). As a source of subsistence for the Senegalese population, it has always been deficient and unable to meet the food needs of the Senegalese population.

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The gap between domestic production and the ever-increasing needs of the population has continued to deepen over the years. In West Africa, Senegal is second only to Mauritania in terms of the difficulty providing sufficient food staples to its people. In fact, Senegal imports 70% of cereals needed and most dairy products, vegetable oils and agri-food products[2]. Despite recent progress in its agricultural production, Senegal is still among the African importing countries net of food products. Nationally, cereal availability is estimated at 1,265,930 tons (rice, maize, millet, sorghum), which represents a 49.1 percent coverage since the estimated requirement is 2,576,870 tons[1].

Like most sub-Saharan countries, the Senegalese climate is characterized by both temporal and spatial variations in precipitation. Under a sunny sky, most of the rainfall on average occurs between June and September and is well spread during the rainy season in the south of the country but more irregular in the northwest part of the country (Thies, Louga, Saint-Louis). Annual precipitation decreases from north to south from 1000 to 200 mm per year[3]. The recurrent floods produced between 1980 and 2012 reached 400,000 to 600,000 inhabitants each year and are responsible for damages estimated at $42 million. The rise of sea level, together with the undesirable salinization of the soil, the harmful erosion of the coast, and desertification represent a real climatic threat in Senegal.

Climate change may jeopardize the expected benefits of agriculture. Studies have predicted that the average global temperature may increase by 1.4–5.8 °C and there would be substantial reduction in fresh water resources and agricultural yield by the end of the 21st century[4]. Rising temperatures are clearly detrimental to seed hatching and crop development or maturity and depress crop yields. The moisture retained in the soil cannot therefore be used in its fullness because to the evaporation of the soil. The increasingly acrid aridity of the soil sharpens the evaporation which eventually disposes of the plants or the crops of their leaves[5].

However, some climate economists [for example, (Cline, 2008)[5]] believe that a modest increase in temperature would be favorable to agricultural yield. Indeed, Climate change may benefit agriculture because carbon dioxide, the main cause of climate change, may be useful to certain crops (wheat, soybean, rice, etc.) by improving photosynthesis[5]. In addition, agriculture is partly responsible for greenhouse gas emissions. According to an OECD report published in 2017, emissions of greenhouse gases from agriculture account for 14% (more than transport emissions and almost industrial emissions) of global emissions. It is, therefore, during these climatic difficulties and food insecurity that the Senegalese government wants to leverage eight levers, aligning intelligent climatic agriculture (AIC 4) with the Emergent Senegal Plan (PSE) and the Program for Strengthening and Accelerating the Cadence of Agriculture in Senegal (PRACAS) through regular exchanges of knowledge among key actors. Therefore, the present study is of real interest to policy makers but also to the many actors in the agricultural sector.

The overall objective of this research is, therefore, to assess the impact of climate change on food crop yields in Senegal. More specifically, it evaluates the impact of an increase in temperature and a decrease in precipitation on the yield of food products. Based on a review of the literature on the link between climate change and agriculture two hypotheses are posited. First, we hypothesize that a rise in temperature reduces the yield of food products; the second hypothesis asserts that a decrease in rainfall reduces the yield of food products.

The rest of our study is divided into four sections. Section 2 presents the methodological approach adopted. Section 3 presents the empirical results of our investigation. Finally, Section 4 discusses the findings and the last section concludes our investigation.

2. Methodology

We use the Factor Augmented Vector Autoregressive (FAVAR) model in this study. Vector Autoregressive (VAR) models have been widely used to evaluate the impulse responses of variables following an impact of one or more specific variables according to the studies. The VAR approach seems to provide a large amount of useful structural information. However, the VAR approach has come under criticism because of the relatively small amount of information it can handle. To maintain degrees of freedom, standard VARs rarely use more than six to eight variables. It is unlikely that this small number of variables covers the range of available information on the issue of climate change and its effects on agriculture. In this study, we overcome this problem by combining standard VAR analysis with factor analysis.

Stock and Watson [6] develop an approximate dynamic factor model to summarize information in large datasets for forecasting purposes. They show that predictions based on these factors exceed univariate autoregressions, small vector autoregressions, and key indicator models in simulated forecasting exercises. Bernanke and Boivin [7] show that the use of estimated factors can improve the estimation of the response function of the FED policy. If a small number of estimated factors effectively summarize large amounts of information, a natural solution to the problem of degrees of freedom in VAR analyzes is

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to increase the standard VARs with estimated factors. In this study, we consider the estimation and properties of FAVAR, and then apply these models to agriculture in a context of climate change.

Let Y_t be an (M × 1) vector of climatic variables. According to the standard approach in the VAR literature, Y_t could contain one or more indicators of shock or climate change, agricultural variables such as cereal yields. The conventional approach involves estimating a VAR, a Structural VAR (SVAR) or another multivariate time series model using data for Y_t alone. However, in many applications, additional economic, climatic, and agricultural information not fully captured by Y_t may be relevant for modeling the dynamics of these series. Suppose that this additional information can be summarized by a (K × 1) vector of unobserved factors, F_t, where K is small.

The joint dynamics of $\left[F_t', Y_t'\right]$ is given by the following transition equation:

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + \vartheta_t \tag{1}$$

Where $\Phi(L)$ is a finite-order delay polynomial d, which may contain a priori restrictions as in the VAR literature. Equation (1) cannot be estimated directly because the Ft factors are not observable. Suppose we have a number of time series, collectively denoted by an (N × 1) vector X_t . The number of time series of information N is large (N may be greater than T, the number of periods) and will be assumed to be much greater than the number of factors and the variables observed in the FAVAR system (K + M << N). We assume that the temporal series of information X_t are related to the unobservable factors Ft and the observed variables Y_t by an observation equation of the form:

$$X_t = \Lambda^f F_t + \Lambda^y Y_t + e_t \tag{2}$$

Where the coefficient related to F_t is an (N × K) factor load matrix and the coefficient related to Y_t is (N × M), and the (N × 1) vector of error terms et is zero mean and is assumed to be normal and uncorrelated.

There are two approaches to estimating equations (1) and (2) The first is a two-stage principal component approach, which provides a nonparametric way of finding the common space covered by the factors of X_t, which we denote by C (F_t, Y_t). The second is a one-step Bayesian parametric approach. These two approaches differ in many dimensions and it is not clear a priori whether one should be favored over the other.

We choose the two-step procedure following Stock and Watson's forecasting exercises [6]. In principle, an alternative is to assume independent normal errors and to estimate equations (1) and (2) jointly by maximum likelihood. However, for very large dimensional models, the irregular nature of the likelihood function makes maximum likelihood estimation impossible in practice. In this case, we consider the joint estimation using Gibbs-based likelihood sampling techniques developed by Geman and Geman[8].

Y_t contains three climatic variables: rainfall, temperature and CO2 emissions. Climate change is thus manifested by a shock on rainfall or temperature. A rainfall shock will therefore be a drop-in rainfall and a thermal shock will be an increase in temperature. Modeling is based on a combination of both agricultural and economic variables. Among the agricultural variables we have, among other things, the yields of the main food crops (maize, millet, sorghum, rice) and the areas devoted to different products. Economic variables include, inter alia, cereal production indices, price indices for maize, millet-sorghum and rice producers, GDP and its deflator, agricultural value added. The data cover the period 1970-2014, a set of 45 observations per time series.

In practice, the number of factors necessary to represent the correlation between variables is generally unknown. In order to determine the number of factors to be considered, an empirical method serving as an information criterion was suggested by Bai and Ng [9]. In our study, the application of this criterion estimates that there is one main factor to consider. Moreover, the selection criteria of the lags lead us to consider 1 lag in the FAVAR model (Appendix 3). Thus, we obtain an autoregressive vector model with 1 increased factor and a delay of one period.

3. Results

This section reports the results of the FAVAR model applied to the impact of climate change on food crop yields by using the code developed by Koop and Korobilis[10][1]. We made two representative shocks to climate change. The first shock is an increase in temperature (thermal shock) and the second, a decrease in rainfall. The shocks are carried out over the year 2014 and the effect and observed over a 10-years horizon. It is therefore necessary to observe the reaction of the target variables (cereal yields,

1 https://sites.google.com/site/garykoop/home/computer-code-2 agricultural added value and others) up to 2024 following each of the two shocks in 2014.

Table 4 in the appendix gives an overview of the target variables in the formation of the Ft factor based on the two-step nonparametric procedure as applied by Stock and Watson [6], Bernanke et al.[11] and Soares[12]. We note that the yield of millet is strongly linked to this factor and has a strong contribution to the formation of this axis. The yields of other agricultural products exhibit correlations greater than 0.5 and have an average contribution on the axis considered. Following the Principal Components Analysis, a priori distributions were assigned to the coefficients and the error term of equation (2). We assume that lambda f and lambda y follow a normal centered law. Furthermore, the error term is assumed to follow a Gamma distribution with parameters a = 0.01 and b = 0.01. Following the Gibbs sampling with 2,000 replications to ensure convergence, we obtain the posterior distributions of the lambda f and lambda y coefficients.

Equation (1) is then estimated by a simple Bayesian VAR using the Normal Wishart priors on the dependent variables (shock variables & main factor) and their delayed values.

4. Discussion

4.1 Thermal Shock: Increase in Temperature

The temperature was rising fast in 2014. The impact will gradually weaken to approach its initial value of zero from the 7th year after the shock as shown in Appendix 1. Before observing the impact of this shock on the target variables, it is important, in a context of climate change, to see the response of rainfall to this thermal shock. The thermal shock is felt on the rainfall from the second period. Thermal shock on rainfall results in an increase in the amount of rainfall, as shown in Appendix 1 in the following year, 2015, where the amount of precipitation reaches its maximum value. After this year the effect remains positive while gradually weakening but more slowly than the weakening of the thermal rise. The return to equilibrium of rainfall will occur only after the 11th year after the shock.

Our findings seem to be at variance with our expectations because an increase in annual temperature is supposed to result in a decrease in the amount of precipitation. But it should be noted, however, that we observe an evolution in the same direction of the two variables in Senegal during the past 3 or 4 years. Indeed, the two climate variables have a linear correlation that is not significantly different from zero. Thus, other factors appear to be at the origin of the evolution of these variables. The results of the variance decomposition of temperature, reported in Table 2, show that own innovations explain about 72.6% of the effect felt in the second period by the rise in temperature. At the end of the horizon, own innovations explain up to 63.4% of the variance of the temperature prediction error is while own innovations explain 2.8% of the variance of the prediction error of rainfall.

A positive shock on temperature gradually affects the yield of cereals. A rise in temperature favors the production of rice, maize and millet, whose yields are clearly increasing. For rice, a positive shock on temperature causes an increase in rice yield which reaches its maximum level in the first year of the shock before quickly weakening and vanishing by the end of the second year after the initial shock. The reaction of maize to shock is almost like that of rice. The impact on maize gradually decreases and dies out by the end of the 10th year after the shock. This is because rice is a very water-intensive crop.

The rise in rainfall caused by thermal shocks significantly increases rice, maize and millet yields. However, since rice needs relatively more moisture, the impact on shocks on it does not cancel as fast.

The impact of thermal shock on millet is like that experienced by maize (yield increase in the first year then progressive decrease of the impact) but the impact on millet is 2 times less important than that obtained for maize.

Global warming, therefore, has a much greater positive impact on maize than on millet. This is consistent with the overall expected results. Thermal shocks cause an increase in precipitation, which is more beneficial to corn than to millet. Indeed, millet is a crop that does not require plenty of water for growth and maturity. Indeed, even a slight amount of rainfall can significantly affect the yield of millet. This explains why the impact of heat shock is less favorable to millet than corn. It should also be noted that the rise in temperature is accompanied by an increase in emissions of greenhouse gases (see appendix), notably CO_2, which makes it possible to improve photosynthesis in crops, justifying once again the increase in yields of millet, maize and rice. On the other hand, global warming does not seem to be beneficial to sorghum. In the first year, the heat shock seems to increase sorghum yield, but the impact quickly becomes negative in the second year. The decline in yield remains slight and quickly approaches its equilibrium level from the 6th year after the shock. So, sorghum do not seem to withstand periods of high temperature. These results are very similar to those obtained by Singh and al.[13].

Finally, a slight decrease in agricultural value added resulting from thermal increase is observed. This is prob-

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ably due to the decline in producers' price for cereals (See Appendix 1).

4.2 Rainfall Shock: Decrease in Rainfall

Analysis of the impulse response functions reveals that temperature undergoes a slight drop that will stagnate over the years to reach its level of equilibrium beyond the 10th year after the shock. This shows that a rainfall shock has a pronounced effect on temperature.

The results of the rainfall variance decomposition, shown in Table 3, reveal that the variance of the rainfall forecast error is due to 66.9% of its own innovations and 7.4% of the innovations of the variance of the temperature prediction error. Regarding the thermal shock scenario, it is observed that the impact of temperature on rainfall is greater than that of rainfall shocks on temperature.

As for greenhouse gas emissions, they decline in the second year after the shock and then return to equilibrium in the long term. Compared to the previous scenario, it appears that the emitted amount of greenhouse gases increases when it is a thermal shock whereas it decreases in the event of a rainfall shock.

From the agricultural point of view, we observe a decline in the yields of all the food products selected in this study. The yields of the different crops generally reach their equilibrium levels from the third year after the shocks suffered. These results support the idea that small amounts of rain result in low agricultural yields. This decline in food crop yields could explain the decline in value added in the agricultural sector. The impact of rainfall shock on the added value fades 3 years later. Falling cereal production output leads to an increase in the price indices of maize, millet and sorghum.

5. Conclusion

The agricultural sector occupies a prominent place in the priority development axes defined by the Government of Senegal. This sector needs considerable improvement given the low yields of cereal crops. Agricultural production, characterized by a more or less favorable climate for fruit and vegetable production, remains vulnerable to price shocks, posing significant risk to food security. This study focuses on the impact of climate change on food crop yields. The study uses a Vector-Auto-Regressive to an Increased Factor (FAVAR) model in order to capture as many as 27 climatic and agricultural variables.

The shock variables used are temperature and rainfall. The empirical estimates show that a rise in temperature is favorable to the cultivation of maize, rice and millet. Rising temperature is explained by the amount of precipitation and greenhouse gas emissions all of which increased as a result of this rise in temperature. In addition, sorghum (essential in the food basket of the poor) is characterized by a significant decrease in yields in the short term following this thermal shock.

A second scenario is based on a fall in the amount of precipitation. From this decline, we see a decline in food crop yields that may explain the higher prices for cereal producers. Climate change could thus be included among variables explaining the cereal price evolution. It should also be noted that gas emissions are increasing in the context of a thermal shock. All in all, we note that the agricultural sector in Senegal, especially food, is highly sensitive to climate change. This sensitivity affects both agricultural yield and grain prices, especially.

Therefore, the agricultural sector, particularly rural, must take measures to adapt to climate change. For example, different varieties of food products that are resistant to rainfall rarity can be introduced to combat seasonal shifts in seed periods. This study can be ameliorated by embracing a disaggregated approach to target the rural and agricultural areas affected by climate change. Thus, it would be useful to construct a model capable of considering long-term variations, although climate change is generally slow.

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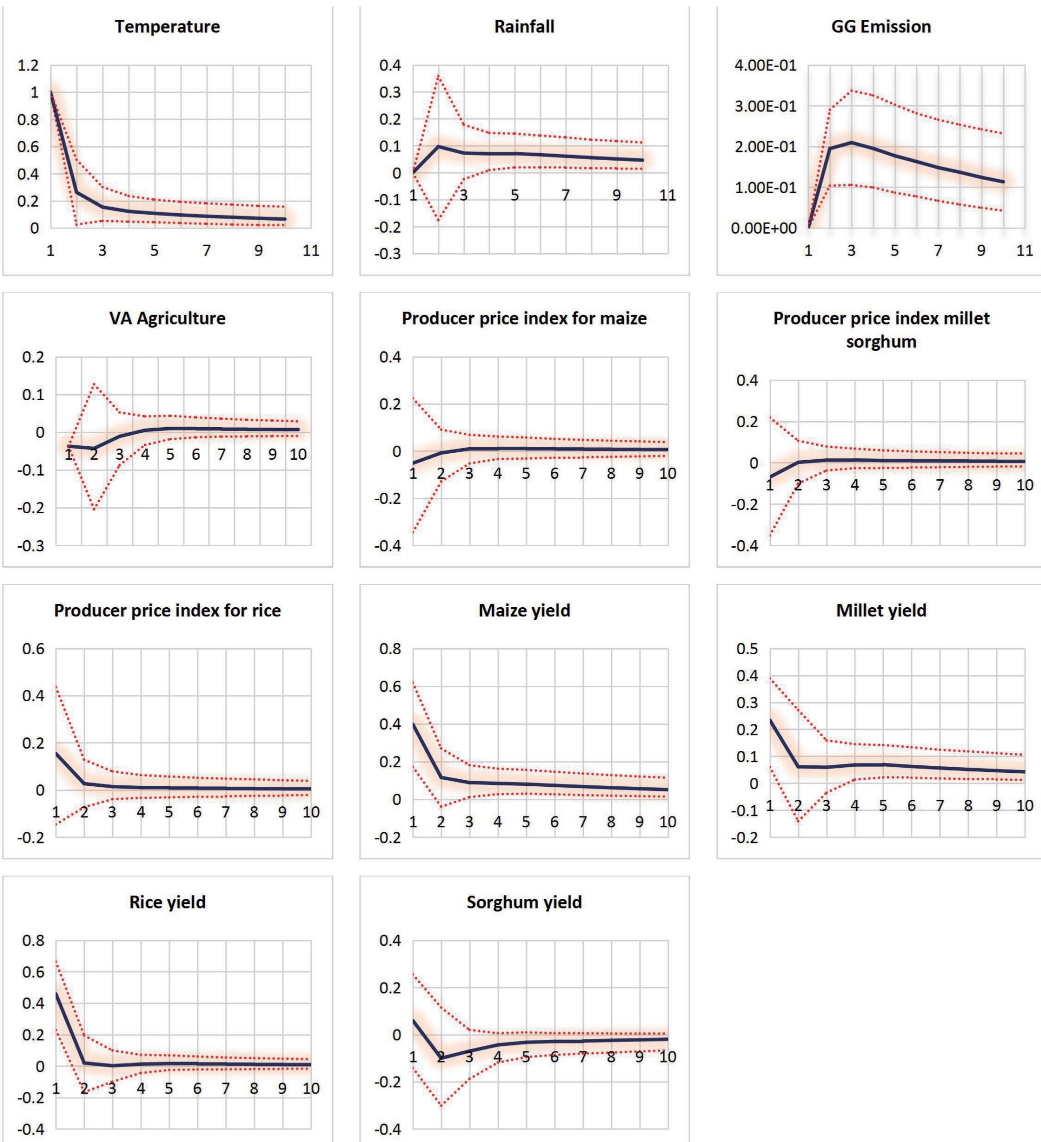
Appendix

Appendix 1(a). Impact of thermal shock on variables



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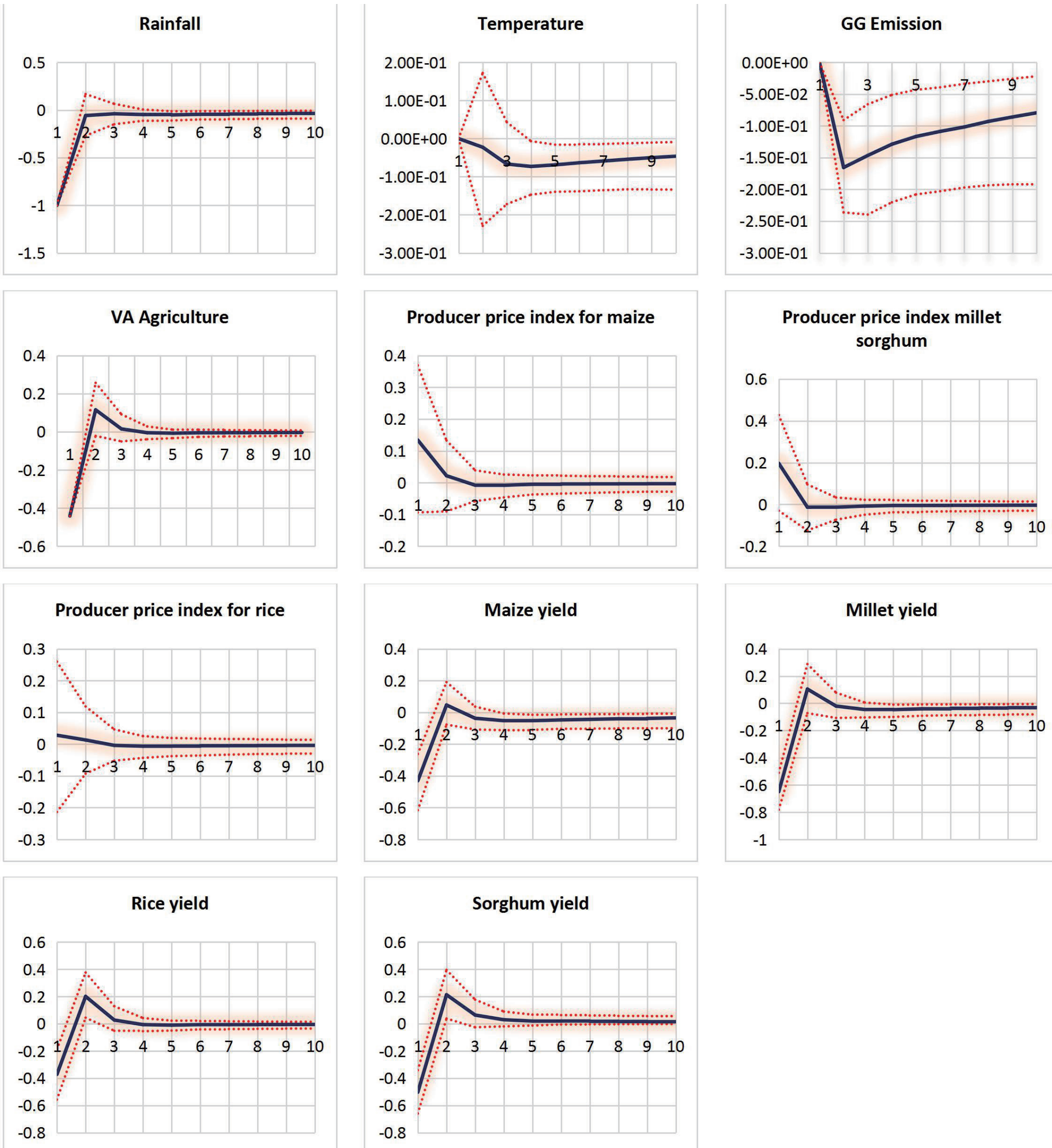
Appendix 1(b). Impact of Rainfall Shock on Variables



Appendix 2(a). Selection of Model's Lag

We used lag selection criteria to specify the optimal lag. The choice of these criteria can be summarized in the following table:

Table 1. Lags selection criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-19.4	NA	0.0	1.5	1.8	1.6
1	10.3	49.8*	0.0*	0.1	0.6*	0.3*
2	13.5	5.1	0.0	0.1	0.8	0.4
3	18.7	7.5	0.0	0.1*	0.9	0.4
4	0.3	2.1	0.0	0.2	1.2	0.6

LogL : sequential modified
LR: test statistic
FPE : Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

(*) Indicates the lag given by the criterion.

Appendix 2(b). Variance Decomposition

Table 2. Variance decomposition of thermal shock (in %)

Periods	Factor 1	GG	RAIN	TEMPERATURE
1	0,0	0,0	0,0	100,0
2	0,2	26,9	0,3	72,6

3	0,8	29,9	1,0	68,3
4	1,2	30,8	1,6	66,3
5	1,5	31,3	2,0	65,2
6	1,7	31,5	2,3	64,5
7	1,9	31,6	2,5	64,0
8	2,0	31,7	2,7	63,7
9	2,0	31,7	2,8	63,5
10	2,1	31,7	2,8	63,4

Table 3. Variance decomposition of rainfall shock (in %)

Periods	Factor 1	GG	TEMPERATURE	RAIN
1	0,0	0,0	0,0	100,0
2	6,0	9,4	0,6	83,9
3	6,4	10,5	1,8	81,4
4	7,2	10,9	2,6	79,3
5	7,8	11,5	3,3	77,4
6	8,4	12,1	4,1	75,4
7	9,1	12,7	4,9	73,3
8	9,8	13,4	5,7	71,2
9	10,5	14,0	6,5	69,1
10	11,2	14,6	7,4	66,9

Appendix 3. List of Model's Variables

N°	Variables		Source	Unit
1	Agriculture value added	*	WDI	2010 At basic price in $
2	Arable land hectares	*	WDI	Hectares
3	Consumption fertilizer	*	FAOSTAT	Ton
4	CO2 emissions of crop residues		FAOSTAT	Kton of CO2
5	Producer price index Corn	*	FAOSTAT	
6	Producer price index millet-sorghum	*	FAOSTAT	
7	Producer price index Paddy rice	*	FAOSTAT	
8	Active population in subsistence agriculture	*	FAOSTAT	1000 persons
9	Maize production		FAOSTAT	Ton
10	Millet production		FAOSTAT	Ton
11	Rice production		FAOSTAT	Ton
12	Production Sorgho		FAOSTAT	Ton
13	Maize yield		FAOSTAT	Hg / Hectare
14	Millet yield		FAOSTAT	Hg / Hectare
15	Rice yield		FAOSTAT	Hg / Hectare
16	Sorghum yield		FAOSTAT	Hg / Hectare
17	Maize seeds	*	FAOSTAT	Ton
18	Millet seeds	*	FAOSTAT	Ton
19	Rice seeds	*	FAOSTAT	Ton
20	Sorghum seeds	*	FAOSTAT	Ton
21	Harvested area of Maize		FAOSTAT	Hectares
22	Harvested area of Millet		FAOSTAT	Hectares
23	Harvested area of Rice		FAOSTAT	Hectares
24	Harvested area of Sorghum		FAOSTAT	Hectares
25	Total greenhouse gas emissions		WDI	Kton of CO2

(*) Slow-moving variables

FAOSTAT: *Food and Agriculture Organization Statistical Databases*

WDI: *World Development indicator*

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