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INDEXING / INDEXATION

EDITOR'S NOTE :

This issue was born out of a shared concern and a consciously embraced sense of hope.

It addresses rice production under increasing climate variability, public procurement systems that shape the effectiveness of public policies, fuel shortages, health systems under strain, the challenge of building endogenous industries, and media narratives capable of fostering both fear and resilience. At the heart of these analyses lies a fundamental question: how can decent living conditions be preserved amid economic, institutional, and social uncertainty?

The contributions brought together in this issue do not remain at the level of theoretical abstraction. They are grounded in concrete realities, agricultural territories, public administrations, cities under pressure, populations facing scarcity, and states striving for sovereignty. They also open a space for ethical reflection, notably through the thought of Emmanuel Levinas, reminding us that any reflection on development entails a responsibility toward others.

This issue does not claim to provide exhaustive answers. Instead, it makes a deliberate choice: to confront the complexity of reality with scientific rigor, critical insight, and intellectual commitment. Here, thinking is never neutral; it is an act of lucidity, sometimes even a form of resistance.

We wish you an engaging read.

The Editor

Dr. Patrice Racine DIALLO

NOTE DE L'ÉDITEUR :

Ce numéro est né d'une inquiétude partagée et d'une espérance assumée.

Il y est question de riz cultivé sous une variabilité climatique croissante, de marchés publics qui conditionnent la réussite des politiques publiques, de pénuries de carburant, de systèmes de santé sous tension, d'industries à construire de manière endogène, et de récits médiatiques capables de nourrir aussi bien la peur que la résilience. Au cœur de ces analyses se pose une interrogation essentielle : comment préserver des conditions de vie dignes dans un contexte d'incertitude économique, institutionnelle et sociale ?

Les contributions réunies dans ce numéro ne s'en tiennent pas à des abstractions théoriques. Elles s'ancrent dans des réalités concrètes : des territoires agricoles, des administrations publiques, des villes éprouvées, des populations confrontées à la rareté, des États en quête de souveraineté. Elles ouvrent également un espace de réflexion éthique, notamment à travers la pensée de Levinas, rappelant que toute réflexion sur le développement engage une responsabilité envers l'autre.

Ce numéro ne prétend pas épuiser les réponses. Il fait un choix clair : affronter la complexité du réel avec exigence scientifique, sens critique et engagement intellectuel. Penser n'y est jamais neutre ; c'est un acte de lucidité, parfois même une forme de résistance.

Bonne lecture.

L'Éditeur

Dr. Patrice Racine DIALLO

CONTENTS

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Effect Of Rice Initiative Programme On Rice Yield Under Climate Variability In Mali

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ABSTRACT

This study estimated the effects of the Rice Initiative Programme (RIPRO) on rice mean yield and its variance under climate variability using the stochastic production function. The study relied on a three-stage feasible generalized least square to estimate a translog production function using panel data which covered climate and non-climate variables on six rice-growing regions from 1987 to 2017. The results showed that the rice initiative programme has positively affected rice mean yield. The results also indicated that climate variability influenced rice mean yield through variables like temperature deviation from its optimal level for rice and diurnal temperature range. Government and its development partners should encourage farmers to adopt improved rice varieties that withstand high temperature, and early sowing practices to avoid the stresses from high temperatures.

Keywords: *Rice Initiative Programme, yield, variance, mean, climate variability.*

Effet du Programme d'Initiative Riz sur le rendement du riz face à la variabilité climatique au Mali

RÉSUMÉ

Cette étude évalue les effets du Programme d'Initiative Riz (RIPRO) sur le rendement moyen du riz et sa variance dans un contexte de variabilité climatique, en utilisant une fonction de production stochastique. L'analyse repose sur une estimation en trois étapes par la méthode des moindres carrés généralisés faisables afin d'estimer une fonction de production translogarithmique à partir de données de panel couvrant des variables climatiques et non climatiques dans six régions rizicoles, sur la période allant de 1987 à 2017. Les résultats montrent que le Programme d'Initiative Riz a eu un effet positif sur le rendement moyen du riz. Ils indiquent également que la variabilité climatique influence le rendement moyen du riz à travers des variables telles que l'écart de température par rapport au niveau optimal pour la culture du riz et l'amplitude thermique diurne.

Le gouvernement et ses partenaires au développement devraient encourager les producteurs à adopter des variétés améliorées de riz capables de résister aux températures élevées, ainsi que des pratiques de semis précoce afin d'éviter les stress liés aux fortes températures.

Mots-clés : *Programme d'Initiative Riz, rendement, variance, moyenne, variabilité climatique.*

INTRODUCTION

Lower yields of heat-sensitive crops may result from rising temperatures, especially in areas that are already experiencing high temperatures (Xu et al., 2025). Droughts and floods brought on by altered rainfall patterns can have a detrimental impact on crop growth and productivity (Kumar et al., 2024). The projected negative effects of climate change on agricultural production, coupled with the challenge of meeting the increasing demand for food resulting from the worldwide population growth deserve particular attention (Harris & Consulting, 2014). In Africa, climate-related hazards create pressure on water resources, and reduce crop yields that negatively affect farm households' livelihoods and undermine their food security (Van Ypersele de Strihou, 2014).

The underperformance of the agricultural sector undermines the incomes of rural people, increases the prices of food, and reduces the job opportunities in this sector (AfDB, 2016). This is making Africa highly dependent on food imports. In 2011, the spending on food imports (excluding fish) in Africa was estimated at $35 billion. In 2013, the undernourished population in Sub Saharan Africa (SSA) was estimated at 23.4 % and expected to increase by about 13.9% by 2050 due to climate change (World Resources Institute, 2013).

The population of Western Africa is currently estimated to be around 500 million, making it a dynamic and rapidly growing demographic group (Izugbara et al., 2024). The population of West Africa is expected to increase from 300 million in 2010 to 450 million in 2025 (FAOSTAT, 2019). Agriculture employed 65% (Hollinger & Staatz, 2015) and provides about 27.17% of the gross domestic product in West Africa (Iheonu et al., 2022). Rice is a major staple food of West Africa; its per capita consumption is expected to rise from 44 kg in 2010 to 53 kg in 2025 (Fofana et al., 2014).

Mali is one of the largest Sahelian countries in West Africa. Its total area reaches more than 1.2 million km². Agriculture is the mainstay of the economy of Mali. In 2017, the share of the country's gross domestic product (GDP) attributed to the agricultural sector was about 40.8% which was the highest share, compared to the industry and services sectors (INSTAT, 2018). The sector employs more than 80% of the workforce and provides 30% of export earnings (INSTAT, 2018). Malian agriculture is generally confronted with climatic and hydrological challenges despite the efforts made to develop irrigation infrastructure.

Rice production in Mali was estimated at 2.7 million tons in 2017 which makes it the second highest rice producer in West Africa after Nigeria (Styger & Traore, 2018). Rice is the major cereal cultivated in Mali. From 2006-2015, Data from CPS/SDR shows that ice is the highest contributor to national cereal production on average (32%) followed by millet (26%). During the same period, the distribution of the national rice production per region shows that on average, the region of Segou provides almost half (49%) followed by the regions of Mopti (23%), Tombouctou (11%), and Sikasso (10%) while the region of Kayes has the smallest share of about 2% of the national rice production (CPS/SDR, 2016).

Cereals are the staple food in Mali. The total cereal consumption was estimated at 4,371,840 tons/year, and rice was the most (30%) consumed cereal (CPS/SDR, 2016). In 2018, rice per capita consumption was estimated at 102 kg/year (Styger & Traore, 2018). In Mali, rice productivity remains low and unable to satisfy the growing population's consumption demand. The rice yield potentially achievable in Mali was estimated between 5 Mt/ha and 8 Mt/ha (Diakite et al., 2016). From 1987 to 2017, the average rice yield was 2.58 Mt/ha (CPS/SDR, 2017) which is below the country's potential yield attainable. In 2014, the rice self-sufficiency rate was estimated at approximately 85% (Kergna & Cisse, 2014) and import from Asia covers the remaining gap. From 2010 to 2016, the annual average import of rice into Mali was estimated at 196,673 metric tonnes (CPS/SDR, 2016). Rice production in Mali faces high year-to-year variability from 1961 to 2014 (Figure 1), which made rice farmers more vulnerable in terms of poverty and food security in the face of climate variability.

In response to the low productivity of rice and its variability, given the growing consumption of rice in Mali, the government launched the Rice Initiative Programme (RIPRO) in 2008, which was followed by the National Rice Development Strategies (NRDS) in 2009 (FAO, 2017). The programmes subsidized seed and fertilizer to rice farmers and facilitated their access to credit for farm equipment and agricultural extension services (FAO, 2017). However, little is known about how the rice initiative programme has affected the rice mean yield and its variance under climate variability. To the best of our knowledge so far, no study has been conducted to assess the effects of RIPRO on mean and variance of rice yield under climate variability in Mali. Therefore, the present research seeks to fill this void by addressing two specific research questions namely: (i) how the RIPRO affects the mean rice yield under climate variability in Mali? and (ii) how the RIPRO affects the variability of rice yield under climate variability in Mali?

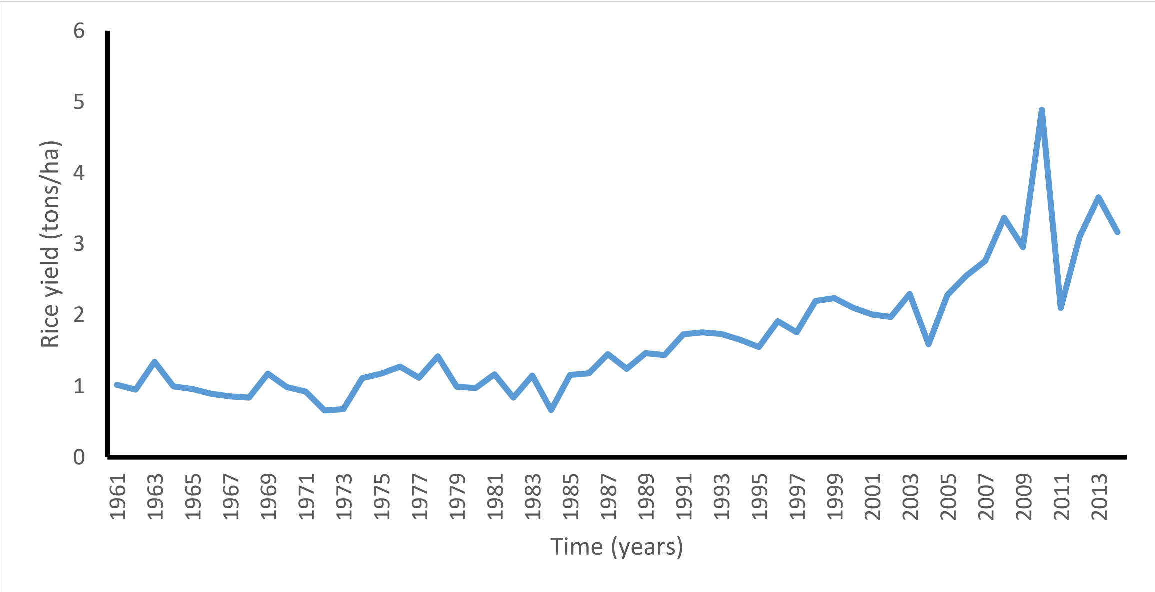

Figure 1: Trends In Cereal Production In Mali, 2006-2015
Source: Constructed by the authors using data from FAOSTAT

The main objective of this research is to assess the effects of RIPRO on mean and variance of rice yield under climate variability in Mali. To answer the above specific questions, the study sets two specific objectives. First, the study estimates the effect of RIPRO on mean of rice yield under climate variability in Mali. Then, the study estimates the effect of RIPRO on variance of rice yield under climate variability in Mali. The next section of the paper is focused on the materials and methods. Then, the empirical results are discussed. The study concludes and provides some policy recommendations in the last section.

METHOD

Theoretical framework

Given the objective of the study, to estimate the effects of RIPRO on rice yield and production risk under climate variability in Mali, we employ the theory of risk. The foundation for theoretical and empirical work on production risk was laid by Just and Pope (1978) as a production function with a risk component called stochastic production function or production risk function. In this function, the risk is measured by the variance of the dependent variable. The stochastic production function assumes that the mean crop yield and its variance are independently explained by the same vector of explanatory variables. Following Just and Pope (1978), the study denotes a stochastic production function as:

$$W(Y_t) = f(X_t) + h(X_t)^{\frac{1}{2}}\epsilon \quad (1)$$

where Y is the crop yield at time t, X is a vector of explanatory variables, ϵ is the error term with zero mean and variance one. The first component of equation (1) is the function of mean or average crop yield E(Y_t) while the second component represents the function of the crop yield variance μ_t. The average and variance of crop yield are expressed as follows:

$$E(Y_t) = f(X_t; \beta) \quad (2)$$

$$\mu_t = h(X_t; \alpha)^{1/2}\epsilon \quad (3)$$

With regard to the specification of a production risk function, an input can be risk increasing, decreasing, or without risk depending on the sign of the first derivative of the yield variance with respect to that input. If the first derivative of the yield variance for an input is greater than zero (or less than or equal to zero) then that input is risk increasing (or risk decreasing or without risk). If the use of an input increases the risk (for example, the use of pesticides), a risk-averse producer will not use or will use less of that input; the true loss of utility for a risk-averse producer will be greater than the risk-neutral producer. If an input contributes to decreasing risk, the risk-averse farmer will use more of it (Just & Pope, 1978). The flexibility in the functional form of the production function is important with risk considerations. An input can increase the risk due to the lack of flexibility in the production function leading to wrong conclusions. In such situations, inaccurate input policies may be put in place (Just & Pope, 1978).

Analytical framework

The objective of RIPRO was to increase rice yield and reduce rice yield variability. RIPRO was implemented through non-climate factors such as subsidizing fertilizer and seeds to rice farmers, and facilitating their access to credit for farm equipment and agricultural extension services. Several studies, dominated by agronomists and economists, have investigated the determinants of yield. Most agronomic models explain yield as a function of climatic variables, and the omission of farm inputs in modeling is to avoid endogeneity bias (Welch et al., 2010). Farmers' decision about investing in inputs is influenced by climate variables. The inclusion of time and district fixed effects is to ensure that the impacts on yield are from the weather variables not the omitted variables in the regression. The idea is to highlight the explanatory power of these climate variables and then, the adaptation opportunity. Different climate factors have been hypothesised to capture the effects of climate variability on crop yield.

Some studies used climate variables like temperature and rainfall in the raw form (Sarker et al., 2013 and Sarker et al., 2012). Based on the fact that climate variability affects crops, in addition to the raw form of temperature and rainfall, other studies used their standard deviation (Poudel & Kotani, 2013; Barnwal & Kotani, 2010). Some other studies also, including Rahman et al. (2017), compute and use indexes (like standardized precipitation index and the diurnal temperature range) using raw climate data. In economics, however, in addition to the climatic factors, the yield is explained by non-climatic variables; mostly the input variables. Based on the literature, the study assumes that the mean rice yield and its variance are influenced by both climatic and non-climatic factors.

Method of analysis

Following Cabas et al. (2010), the study used the stochastic production function to estimate the effects of RIPRO on the mean of rice yield and its variance under climate variability. As proposed by Just and Pope (1978), the effects of explanatory variables were captured on both the mean of rice yield and its variance. The model is expressed as follows:

$$Y_{it} = f(X_{it};\ \beta) + h(X_{it};\ \alpha)^{\frac{1}{2}}\epsilon \tag{4}$$

where Y_{it} was the rice yield for region i at time t, X represented a vector of explanatory variables (climate and non-climate), β and α were the parameters to be estimated, ϵ was a stochastic error with zero mean and variance one. The first argument of equation (4) captured the effects of explanatory variables on mean rice yield E(Y)=f(X) while the second argument measured the effects of the explanatory variables on rice yield variance V(Y)=h(X). The rationale behind this specification is to spread the effects of explanatory variables on output mean and its variance, independently. So, equation (4) can be rewritten as follows:

$$Y_{it} = f(X_{it};\ \beta) + \mu_{it} \tag{5}$$

$$\mu_{it} = \epsilon_{it}\ h(X_{it};\ \alpha)^{\frac{1}{2}} \tag{6}$$

The mean and the variance of the rice yield were expressed, respectively, as follows:

$$E(Y_{it}) = f(X_{it};\ \beta) \tag{7}$$

$$V(Y_{it}) = Exp\big(h(X_{it};\ \alpha)\big) \tag{8}$$

Two estimation techniques have been highlighted in the literature for the model of Just and Pope (1978). The first estimation technique is the three-stage feasible generalized least squares (FGLS) (Sarker et al., 2013; Poudel & Kotani, 2013; and Cabas et al., 2010). The second estimation technique is the maximum likelihood (Carew et al., 2017; Chen et al., 2004), which is known to be unbiased and more efficient with small samples (Saha et al. , 1997). Given the relatively large size of the sample, the study used the FGLS estimation which is based on the three-stage procedure. The first stage was to estimate equation (5) through ordinary least squares. The second stage used the log of the square of the residual from the first stage to estimate the parameters of equation (6). The parameters of equation (6) are consistent and asymptomatically efficient. The third stage was the weighted least squares which used the inverse of the exponential of the residual of the second stage as a weight to estimate the mean yield from equation (7). This last stage allows for correcting the heteroskedasticity of the error term.

Description of data and data sources

The description of variables used to analyse the effect of the rice initiative programme on rice mean yield and its variance under climate variability with their expected signs are presented in Table 1. The dependent variable was the rice yield Y, which is defined as rice output per unit land area and it is measured in kg per hectare. The independent variables included non-climate, climate, and dummy variables. The non-climate variables were labour, orgfert, inorgfert, and the time trend, which accounts for technological change. The climate variables were the effective rainfall, maximum temperature, temperature deviation from 32 °C, which was considered as the harmful threshold for rice growth, the standardized precipitation index (SPI), and the diurnal temperature range (DTR). The dummy variables included were shock, defined as economic shocks taking 1 during the year when a shock happened and 0 otherwise; RIPRO, defined as a dummy variable for RIPRO taking 0 before the intervention (1987 to 2008) and 1 under the intervention (2009 to 2017); and unobservable regional specific effects dummies (Udi's).

The non-climate variables are all expected to be positive in the yield function and their expected sign in the variance function is ambiguous. The initial climate variables encompassed total precipitation, and temperature which are measured, respectively, in millimeters, and degree Celsius. The effective rainfall, temperature deviation, standardized precipitation index (SPI), and Diurnal temperature range (DTR) were constructed using the initial climate variables. The temperature variability was measured by the temperature deviation and the diurnal temperature range while the rainfall variability was measured by the SPI.

The study used USDA-SCS method since the data available on the precipitation are average annual monthly precipitation. USDA-SCS has been also used by Chapagain & Hoekstra (2010). The expected sign of effective rainfall is positive for the yield function and negative for the variance function. While the expected sign of temperature is unclear for both yield and variance function. The maximum temperature that is optimum for rice production ranges between 27 °C to 32 °C (Rathnayake et al., 2016). The study considered any temperature beyond 32 °C as a deviation from the maximum temperature that is optimum. The expected sign of the temperature deviation is negative for the yield function and positive for the variance function. Following Rahman et al. (2017) as proposed by McKee et al. (1993), the study used the standardized precipitation index (SPI).

The SPI represents the number of standard deviations that the observed total precipitation for year i deviates from the long-term average. The expected sign of SPI is negative for the yield function and positive for the variance function. Diurnal temperature range (DTR) is defined as the difference between maximum temperature and minimum temperature. The expected sign of DTR is negative for the yield function and positive for the variance function. The expected sign of RIPRO dummy is positive for the yield function and negative for the variance function. The expected sign of unobservable regional specific effects dummies (Udi's), and economic shocks dummies (Shocki's) is negative for the yield function and positive for the variance function.

Table 1: Description Of The Variables Used For The Analysis

Variable	Description	Expected sign on rice: Mean yield	Expected sign on rice: Variance
	Dependent variables		
Yield	Mean and Variance of rice production per land area (kg/ha)		
	Explanatory variables		
Labour	Proportion of agricultural population engaged in rice production (individuals/ha)	+	+/-
Organic fertilizer	Quantity of organic fertilizer used in rice production (kg/ha)	+	+/-
Inorganic fertilizer	Quantity of inorganic fertilizer used in rice production (kg/ha)	+	+/-
Effective rainfall	The total precipitation (P_t) during the production season converted into effective rainfall using USDA-SCS approach: $P_e = \begin{cases} \frac{P_t}{125 * (125 - 0.2 * P_t)} & for\ P_t \leq 250mm \\ 125 + 0.1 * P_t & for\ P_t \geq 251mm \end{cases}$	+	-
Temperature	The average maximum temperature (°C)	+/-	+/-
Temperature deviation	Tempdev= Average maximum temperature-32°C	-	+
Standardized precipitation index (SPI)	SPI = $(P_t - lonterm\ mean\ of\ P_t)/standard\ deviation\ of\ the\ mean$	-	+
Diurnal temperature range (DTR)	DTR = Maximum temperature - Minimum temperature	-	+
Rice initiative programme (RIPRO) dummy	RIPRO dummy took value 0 from 1987 to 2008 (before the intervention) and 1 from 2009 to 2017 (after the intervention)	+	-
Unobservable regional specific effects dummy (Udi)	Udi is a dummy taking value 1 for region i (i varies from 1 to 5) and value 0 otherwise.	-	+
Economic shocks dummy	shocki is a dummy taking value 0 for region i (i varies from 1 to 6) during the normal year, and 1 during the year where a shock happened	-	+
Trend	Time trend accounted for technological change	+	+

Source: constructed by the authors

The study used secondary and primary data. Secondary data was collected from various sources. The data include climate and non-climate variables for six rice-growing regions namely Kayes, Koulikoro, Sikasso, Segou, Mopti, and Tombouctou from 1987 to 2015. The climate data was collected from the meteorological service in Mali. The climate data encompasses the average annual monthly temperature and precipitation. The average annual monthly precipitation was used to estimate effective rainfall.

The non-climate data was from the Agricultural Survey of Conjuncture. This data was collected by planning and statistical unit annually on rice (both irrigated and rainfed) and aggregated at the regional level. They include yield, labour, inorganic, and organic fertilizer from 1987 to 2015.

Empirical model specification

The estimation technique used allows estimating both the mean rice yield and its variance. The study did not consider the natural logarithmic forms of variables such as SPI, tempdev, and DTR to avoid the issue of missing value because of the zero value cases. The natural logarithmic forms of the variables such as yield, labour, orgfert, inorgfert, effrain, and temp were considered for the econometric specification. The empirical specification of the mean rice yield for region i at time t; t∈[1987;2017]; i∈[1;6] (1 for Kayes region, 2 for Koulikoro region, 3 for Sikasso region, 4 for Segou region, 5 for Mopti region, 6 for Tombouctou rgion) is given by equation (9):

$$lnYield_{it} = \delta_0 + \delta_1 \ln labour_{it} + \delta_2 \ln orgfert_{it} + \delta_3 \ln inorgfert_{it} + \delta_4 \ln effrain_{it} + \delta_5 \ln temp_{it} + \delta_6 trend + \delta_7 shock1 + \delta_8 shock2 + \delta_9 shock3 + \delta_{10} shock4 + \delta_{11} shock5 + \delta_{12} shock6 + \delta_{13} RIPRO + \delta_{14} tempdev_{it} + \delta_{15} SPI_{it} + \delta_{16} DTR_{it} + \varepsilon \quad (9)$$

The dependent variable (Y) and the variables (X) are in the natural logarithm form; therefore, the coefficient of X measures the elasticity of Y with respect to X, that corresponds to the percentage change in Y as a result of one percent change in X (Gujarati, 2004, p.176). The dummy variables are not in the natural logarithm form, their coefficients $\delta_i's$ are not directly interpreted as a percentage change. The accurate way is to compute the percentage change using the formula $(exponential^{\delta_i} - 1) * 100$ (Wooldridge, 2013, p.235)

Panel properties of data used

The panel data analysis requires the unit root test to avoid spurious regression. This study used the unit root test proposed by Im et al. (2003) since it allows for region-specific effects (Chen et al. 2004). The unit root test results from Im et al. (2003) procedure are summarized for rice yield, labour, organic fertilizer, inorganic fertilizer, effective rainfall, and temperature in Table 2. The null hypothesis is: "All panels contain unit roots" against "Some panels are stationary". The null hypothesis was rejected at level, for all rice yield, labour, inorganic fertilizer, effective rainfall, and temperature. Therefore, these variables were stationary at level. The null hypothesis was rejected at the first difference for organic fertilizer, this variable was stationary at order one. Therefore, the first difference of organic fertilizer was considered in the estimation. The first difference of the natural logarithmic of an economic variable corresponds to the growth rate of that variable in its level form (Gujarati, 2004, p.176). Therefore, the first difference of lnorgfert (noted Dlnorgfet) represented the annual growth rate of organic fertilizer.

Table 2: Im-Pesaran-Shin Panel Unit Root Test

Variables	ADF statistic	p-value	Stationarity
LnYield	-1.912	0.028	I(0)
LnLabour	-3.24	0.001	I(0)
Lnorgfert	-0.239	0.405	I(1)
Lninorgfert	-6.079	0.000	I(0)
Lneffrain	-4.225	0.000	I(0)
Lntemp	-4.505	0.000	I(0)

Source: Constructed by the authors

Hausman specification test was applied to determine whether the fixed effect or the random effect model is the suitable model for the panel data. The null hypothesis under the Hausman specification test states that there is no substantial difference between the random effect and the fixed effect. The result of the Hausman specification test is summarized in Table 3 below. The p-value of the chi-square for Hausman specification test was less than one percent as indicated in table 3. Therefore, the null hypothesis was rejected at 1%. The fixed effect model is suitable for the estimation. This means that the unobservable regional specific effects are different from zero.

Table 3: Hausman Specification Test

H0: Random effect model is the appropriate one / Ha: Fixed effect model is the appropriate one	
Chi2(7) = (b-B)'[(V_b-V_B)^(-1)](b-B)	1071.91
Probability > chi2	0.0000
Decision rule	Prob(chi2) < 1%, rejection of H0

Source: Constructed by the authors

The unobservable regional specific effects have to be considered in the final specification of the model. All the six regions cannot be included in the model because of the dummy trap. Segou region is the highest contributor to national rice production and was used as a reference.

The three-stage FGLS was run for the Cobb-Douglas (CD) and the Translog (TL). The likelihood ratio test favored the Cobb-Douglas (CD) functional form against the Translog for the estimation of rice mean yield while the R-square test favored the Translog functional form (0.31) over the Cobb-Douglas functional form (0.14) for the estimation of the variance of rice yield. For the estimation of the variance of rice yield, the probability of F-statistics was also highly significant with the Translog functional form (1%) and it was not significant with the Cobb-Douglas functional form meaning that globally the explanatory variables did not explain the model. The study is interested in estimating both the mean and the variance of rice yield. Therefore, the study kept the Translog functional form to estimate both the mean and the variance of rice yield. The results of likelihood ratio tests are summarized in Table 4.

Table 4: Likelihood Ratio Test For Nested Models

Models	Restricted Model	Unrestricted model	LRc= -2(lnLR-lnLU)	Degree of Freedom (df)	LRt(df; 0.01)	LRc>LRt reject H0 (H0: Restricted model is the appropriate one)	Best Model
CD is nested within TL	372	265	-214	15	30.58	LRc<LRt	CD

NB: LnLR, LNLU, LRc, and LRt are respectively log likelihood of the restricted model, log likelihood of the unrestricted model, likelihood ratio calculated, and likelihood ratio tabulated.
Source: Constructed by the authors

Study area

The present study is focused on six regions namely Kayes, Koulikoro, Sikasso, Segou, Mopti, and Tombouctou. Basically, these six regions are the major rice-growing areas in Mali. Figure 2 represents the map of the study area.

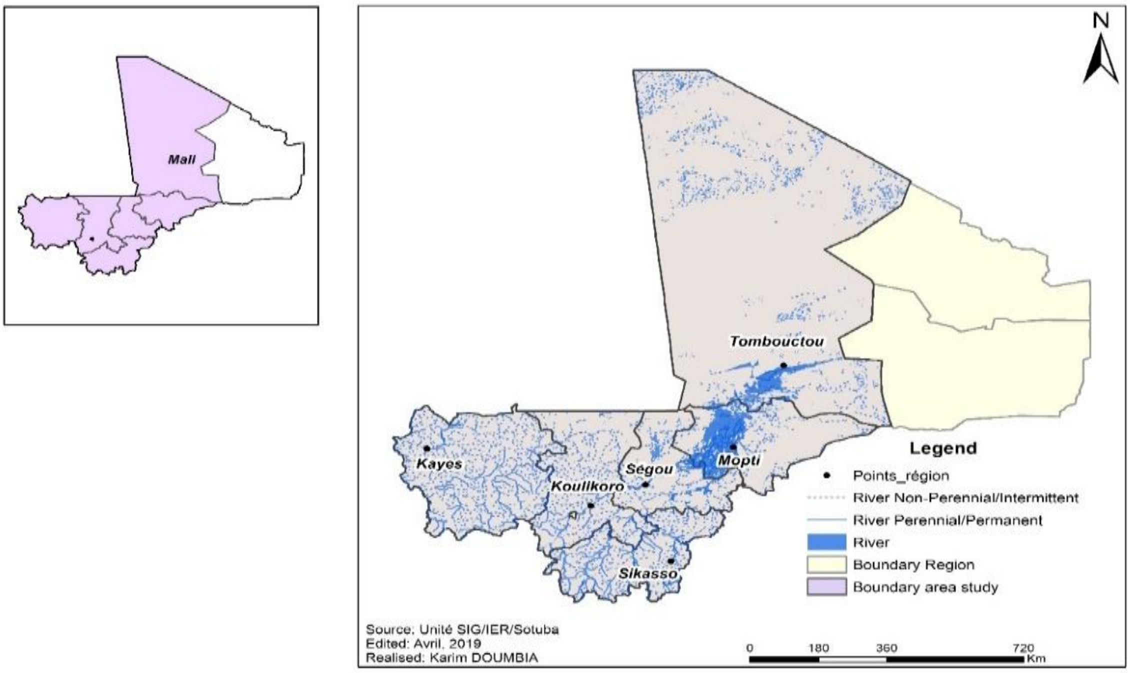

Figure 2: Map Of The Study Area
Source: SIG unit, August 2019

RESULTS AND DISCUSSION

Descriptive statistics

The descriptive statistics of the non-climate variables (rice yield, labour, organic fertilizer, and inorganic fertilizer) for the six regions are reported in Table 5. The rice initiative programme (RIPRO) was launched in 2008. The study divided the sample into two groups: before (1987-2008) and after (2009-2017) the rice initiative programme (RIPRO). The study compared the two groups using the t-test of difference in means. The descriptive statistics include the mean, the standard deviation (SD) in brackets, and the significance level of the t-statistics in the superscript (a,b,c). The mean difference between the rice yield after and before the intervention is positive for all the regions, and statistically significant for all the regions except the region of Kayes. This means that the average rice yield has increased in all the regions with the RIPRO. However, before the RIPRO, the region of Segou had the highest average rice yield (3,474 kg/ha), while the region of Mopti had the lowest average rice yield of 1,113 kg/ha. After the intervention, the region of Kayes has the highest average rice yield (6,882 kg/ha) followed by Segou region (5,239 kg/ha), while Sikasso region has the lowest average rice yield (2,860 kg/ha). For the full sample, the region of Segou has the highest average rice yield (3,986 kg/ha) followed by the region of Tombouctou (2,831 kg/ha). The region of Mopti has the lowest average rice yield (1788 kg/ha).

The mean difference between the labour after and before the intervention is negative for all the regions and statistically significant at 1% for the regions of Kayes and Koulikoro, and 5% for the regions of Sikasso and Tombouctou. This means that the number of labour units used in rice production per hectare has decreased with the RIPRO. Regardless of the intervention, the labour used in rice production per hectare for the region of Kayes is the highest. This result could be explained by the fact that agricultural production in Kayes region is less mechanized, more than 85% of the weeding activity is realized manually or semi-manually, while in the regions of Sikasso, Segou, Koulikoro, and Mopti 70 to 90% of the weeding activity is mechanized or semi-mechanized (CPS/SDR, 2013). Except the region of Tombouctou, the other regions have more agricultural equipment (tractors, Plough, traction oxen, Donkey, cart, etc.) compared to the region of Kayes (CPS/SDR, 2013). However, less than half of the farms (42.5%) have complete hitch equipment (2 traction oxen, a cart with a donkey, and at least one plough) in Mali (CPS/SDR, 2013). The region of Sikasso has the highest number of farms with complete hitch equipment (64.6%). The region of Segou follows with 60.2% of the farms having complete hitch equipment, the region of Koulikoro with 55.4%, the region of Mopti with 37%, the region of Kayes with 18% and the region of Tombouctou with 2% (CPS/SDR, 2013).

The mean difference between the organic fertilizer after and before the intervention is positive and statistically significant at 1% for the regions of Koulikoro and Kayes, and 5% for the regions of Sikasso and Segou. The reduction in the use of organic fertilizer after the intervention could be explained by the high presence of women in rice production in the regions of Koulikoro and Sikasso. Most of the new irrigation infrastructures are located in these two regions. The financial partners of the state impose on the state to prioritize the vulnerable groups (women and youth) in the allocation of the new irrigation infrastructures. Women have limited access to organic fertilizer because it is controlled by the household head (generally men) who rather preferred to reallocate it in their other farms such as cotton, hence reducing the proportion of organic fertilizer allocated to rice production. For the full sample, the region of Mopti has the highest average organic fertilizer application rate (1,183 kg/ha) followed by the region of Sikasso (1,044 kg/ha). In Mali, the main source of organic fertilizer is the livestock manure and Mopti and Sikasso are among the main regions producing the livestock.

The mean difference between the inorganic fertilizer after, and before the intervention is positive and statistically significant for all the regions. This means that the RIPRO has led to increasing the use of inorganic fertilizer on average in all the regions. For the full sample, the region of Sikasso has the highest average inorganic fertilizer application rate (151 kg/ha) followed by the region of Segou (105 kg/ha). The region of Kayes and Tombouctou have the lowest average inorganic fertilizer application rate (52 kg/ha and 26 kg/ha, respectively). This result could be explained by the fact that the region of Sikasso is an excellent agricultural area which contributes greatly to agricultural production in general. The region of Sikasso intensively uses inorganic fertilizer. For instance, during the 2012/2013 cropping season in Mali, about 43% of the amount that farms committed to purchase fertilizers (more than 61.2 million USD) came from the region of Sikasso, 22% from the region of Koulikoro and 20% from the Segou region (CPS/SDR, 2012/2013). The regions of Kayes (8%) and Mopti (7%) have the lowest shares (CPS/SDR, 2012/2013).

Table 5: Descriptive Statistics Of The Non-Climate Variables

Variables		Regions					
		Kayes	Kouli-koro	Sikasso	Segou	Mopti	Tombouc-tou
Yield (kg/ha)	Before RIPRO	1151 (552)	1422 (477)	1827 (1157)	3474 (905)	1113 (366)	2103 (847)
	Under RIPRO	6882 (13331)	3143 (1013)	2860 (712)	5239 (3961)	3438 (788)	4609 (1647)
	Mean Difference	5731	1720[a]	1032[a]	1764	2325[b]	2506[a]
	Full sample	2814 (7389)	1922 (1031)	2127 (1140)	3986 (3986)	1788 (2101)	2831 (1601)
Labour (individual s/ha)	Before RIPRO	173 (123)	29 (23)	11 (9)	3.18 (0.36)	3 (0 .91)	4 (1.95)
	Under RIPRO	62 (47)	11 (7)	8 (3)	2.61 (1.55)	2 (2.2)	2 (1.53)
	Mean Difference	-111[a]	-18[a]	-3[b]	-0.56	-1	-2[b]
	Full sample	141 (117)	24 (21)	10 (7)	3.02 0.9	2	3 (1.95)
Organic fertilizer (kg/ha)	Before RIPRO	53 (13)	1151 (408)	1105 (348)	65.24 (5.25)	1113 (235)	234 (93)
	Under RIPRO	64 (6)	547 (121)	895 (184)	72.38 (10.63)	1352 (680)	262 (140)
	Mean Difference	11[a]	-603[a]	-210[b]	7.15[b]	239	27
	Full sample	56 (12)	976 (445)	1044 (321)	67.31 (7.76)	1183 (417)	242 (107)
Inorganic fertilizer (kg/ha)	Before RIPRO	45.72 (23.29)	69.55 (17.61)	117.14 (46.48)	82.5 (43.57)	51.09 (18.45)	16.09 (19.55)
	Under RIPRO	68.78 (25.38)	151 (28.54)	234.67 (29.95)	160.44 (69.67)	83.56 (6.84)	49.67 (14.19)
	Mean Difference	23.06[b]	81.45[b]	117.53[a]	77.94[a]	32.46[a]	33.58[a]
	Full sample	52.42 (25.78)	93.19 (491)	151.25 (68.5)	105.13 (62.58)	60.52 (21.8)	25.84 (23.69)

NB: a,b,c represents the significance level of t-statistics at 1%, 5%, and 10% respectively.
Source: Author's calculations using data from planning and statistical unit (CPS)

The descriptive statistics of the climate variables for the six regions from 1987 to 2017 are reported in Table 6. It includes the mean and standard deviation in brackets. On average, the rainfall is more effective in the region of Sikasso (208.2 mm/raining season) which is followed by the region of Koulikoro (198.5 mm/raining season). The region of Tombouctou has the lowest effective rainfall (117.5 mm/raining season). The standard deviation for the effective rainfall is greater than one for all the regions meaning that the effective rainfall varies from one season to another in all the regions. On average, the region of Tombouctou has the highest temperature (38.73 °C), while the region of Sikasso has the lowest (30.99 °C). The standard deviation for the temperature is close to one or above one for all the regions which means that the temperature fluctuates from one season to another in all the regions.

Table 6: Mean And Standard Deviation Of The Climate Variables Used In The Regression

Variables	Kayes	Koulikoro	Sikasso	Segou	Mopti	Tombouctou
Effective rainfall (mm)	179.9 (14.19)	198.5 (33.82)	208.2 (16.05)	176.6 (12.31)	166.9 (10.7)	117.5 (29.64)
Temperature (°C)	34.8 (0.99)	35.13 (1.05)	30.99 (1.46)	34.16 (1.25)	33.32 (4.58)	38.73 (0.67)

Source: Authors' calculations using data from the meteorological service in Mali

Estimation results

This section presents and discusses the results of the estimation of the effect of rice initiative programme on mean and the variance of rice yield under climate variability. For the rice mean yield estimation, the dependent variable was the natural logarithm of rice yield while for the estimation of the variance of rice yield, the dependent variable was the natural logarithm of the error term of the rice yield. Both estimations (mean and variance of rice yield) have the same independent variables.

For the rice mean yield estimation, the model fitness indicated that the value of the log-likelihood was 264.51. The Wald statistic was 12137.75 and it was statistically significant at 1%, which means that overall, the explanatory variables explain the mean rice yield indicating that the model is well specified. For the estimation of the variance of rice yield, the model fitness showed that the R-squared is 0.312 which means that 31.2% of the variations of the rice yield variance were explained by the variation of the explanatory variables. The F-statistic was significant at 1% indicating that globally the explanatory variables explain the model.

The results of the rice mean yield presented in Table 7 showed that labour influences positively and statistically (1%) the mean rice yield meaning that yield increases with labour. One percent increase in labour leads to an increase in the mean yield of rice by 0.47 percent. The rice production involves lots of activities (such as transplanting, weeding, and harvesting) which have to be carried out by labour when the mechanization level is low. This result could be explained by the fact that most of the farms do not have mechanical equipment, only 43% of farms have complete hitch equipment (CPS/SDR, 2013). The complete hitch equipment includes 2 traction oxen, a cart with a donkey, and at least one plough.

Miyamoto et al. (2012) analysed the determinants of new rice for Africa (NERICA) yield in Uganda. They also found a positive relationship between rice yield and labour. In developing countries, agriculture is dominated by small farmers who are not well-endowed with capital, therefore they practice labour-intensive agriculture.

The interaction term between labour and temperature was negatively associated with yield. One plausible explanation of this result is that when the temperature is high, workers' efficiency is reduced due to disease and tiredness. The interaction term between labour and effective rainfall was negatively associated with yield. During the rainy season, generally, the rainfall is not well distributed in Mali, it can rain all day without stopping. For instance, an intensive rain reduces farmers' efficiency which could have a negative effect on the rice yield.

The organic fertilizer was affecting negatively and statistically (1%) the rice mean yield. This result could be explained by the fact that the effect of organic fertilizer on the yield is not immediate after the application. The effect will be observed gradually by improving the soil properties over the years. The use of organic fertilizer considerably influences the physical, chemical, and biological properties of the soil (Paul et al., 2016, 2014) resulting to increase the nutrients and water available for the crop in the long-run (Okalebo et al., 2006).

The interaction between organic fertilizer and temperature was positively and statistically (1%) associated with the mean yield of rice. This result could be explained by the fact that the temperature may facilitate the decomposition of organic fertilizer. The interaction between organic fertilizer and effective rainfall was positively and statistically (5%) associated with the mean yield of rice. This result could be explained by the fact that the effective rainfall may facilitate the absorption of the nutrients from the organic fertilizer by the rice plants. From the agronomic perspective, the decomposition process of organic fertilizer is accelerated with high temperature under flooded conditions compared to the non-flooded conditions (Benbi & Khosa, 2014).

Table 7: Results Of The Regression Of Rice Mean Yield And Its Variance

VARIABLES	Mean rice yield	Variance of rice yield
Labour	0.47 (0.064)***	0.114 (0.911)
Labour square	-0.063 (0.06)	-0.41 (0.701)
Labour*Organic fertilizer	0.072(0.044)	1.335 (0.608)**
Labour*Inorganic fertilizer	-0.023(0.036)	0.153 (0.434)
Labour*Temperature	-2.776 (0.321)***	0.479 (5.259)
Labour* Effective rainfall	-0.421 (0.216)*	-2.249 (3.162)
Organic fertilizer	-0.144 (0.053)***	0.749 (0.735)
Organic fertilizer square	0.078 (0.055)	-1.837 (0.835)**
Organic fertilizer *Temperature	2.393 (0.248)***	-3.231 (3.497)
Organic fertilizer * Effective rainfall	0.348* (0.211)	0.026 (2.92)
Organic fertilizer *Inorganic fertilizer	0.117 (0.021)***	0.154 (0.294)
Inorganic fertilizer	0.316 (0.049)***	0.118 (0.94)
Inorganic fertilizer square	-0.086 (0.024)***	0.238 (0.412)
Inorganic fertilizer *Temperature	-0.437 (0.229)*	-9.216 (4.036)**
Inorganic fertilizer * Effective rainfall	-0.056 (0.174)	-6.022 (2.201)***
Effective rainfall	-0.208 (0.432)	11.45 (5.918)*
Effective rainfall square	-0.217 (0.388)	-4.664 (5.406)
Effective rainfall* Temperature	-4.32 (2.234)*	28.19 (28.08)
SPI	0.011 (0.047)	-0.102 (0.63)
Temperature deviation	-1.166 (0.575)**	-3.678 (8.473)
DTR	-0.039 (0.007)***	-0.0716 (0.091)
RIPRO dummy	0.27 (0.042)***	1.081 (0.679)
Trend	0.04 (0.003)***	-0.046 (0.046)
Constant	-0.159 (1.44)	10.92 (21.03)
Observations	180	180
Number of regions	6	6
Log likelihood	264.51	-
Wald chi2 (37)	12137.75	-
Prob (chi2)	0.000	-
R-squared	-	0.312
F-statistics	-	1.8
Prob (F)	-	0.008

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Source: Authors' calculations using Secondary data

Inorganic fertilizer was influencing positively and statistically (1%) the rice mean yield while its square negatively affects the rice mean yield with a 1% significance level. Inorganic fertilizer is non-monotonic.

This means the application of inorganic fertilizer is beneficial for the rice yield up to an optimal level after which it has an adverse effect on rice yield. From the agronomic perspective, the optimal application rate of fertilizer varies by rice-based system. In Sub-Saharan Africa, for the rainfed (lowland and upland) rice-based system, the recommended rate for nitrogen (N) fertilizer ranges from 50 to 80 kg/ha, for phosphorus (P) fertilizer from 13 to 25 kg/ha, and for potassium (K) fertilizer from 10 to 20 kg/ha (Bado et al., 2018). For irrigated lowland rice-based system, the recommended rates vary between 60 and 120 kg/ha for N fertilizer, between 20 and 25 kg/ha for P fertilizer, while the application rate for K fertilizer depends on K contents from water and dust depositions (Bado et al., 2018). This result could be explained by the fact the excessive application of inorganic fertilizer increases the acidity of the soil which affects negatively the rice yield. Miyamoto et al. (2012) also found that the use of nitrogen increases NERICA yield in Uganda.

The association of inorganic and organic fertilizers was beneficial for the rice mean yield. This interaction term is statistically significant at 1%. This result could be explained by the fact that the use of inorganic fertilizer has an immediate effect on the mean yield of rice while organic fertilizer restores the soil. The growth and development of rice plants, productivity, and quality of the crop can be improved through the combination of organic and inorganic fertilizers (Dass et al., 2017 and Paul et al, 2014).

The temperature deviation from the optimal maximum temperature (32 °C) for rice was negatively affecting the rice mean yield. This result could be explained by the fact that high temperature negatively affects the growth and the productivity of rice plant (Krishnan et al., 2011and Yoshida, 1981). Any temperature above 30 °C can be critical for rice and the severity of the damage depends on the growth stage (Krishnan et al.,2011). The diurnal temperature range (DTR) was negatively and statistically (1%) affecting the rice mean yield. The diurnal temperature range represents the daily heat. An increase in daily heat was found to be harmful to the yield. Rahman et al. (2017) also found a negative association between rice yield variability and DTR in Bangladesh.

The results indicated that Rice Initiative Programme (RIPRO) dummy influences positively and statistically the mean of rice yield. The computed percentage change from the coefficient of RIPRO dummy was 31 which means that the mean rice yield has increased by 31% percent as a result of RIPRO. One of the focus of the Rice Initiative Programme is to increase rice farmers' access to agricultural extension services. Agricultural extension agents teach farmers good agricultural practices which help them to increase rice yield. Subsidized fertilizers also are provided through RIPRO, and their use increases rice yield. The increase in productivity is highly dependent on fertilizers (Bado et al., 2018).

The results of the variance of rice yield estimation in the last column of Table 7 showed that the interaction between inorganic fertilizer and effective rainfall was linked negatively to the variance of rice yield. This result could be explained by the fact that effective precipitation may facilitate the nutrient fixation of inorganic fertilizer to the soil. When the rainfall is well distributed, inorganic fertilizer cannot be drained away from the soil by leaching. As a result, rice plants can benefit from nutrients of the inorganic fertilizer which could decrease the rice yield variability. The interaction between inorganic fertilizer and temperature was also decreasing the variability of rice yield. The organic fertilizer square explained the variance of rice mean yield negatively and statistically (5%). The application of organic fertilizer in abundant quantity restores the soil properties which can have a beneficial effect on the variance of rice yield due to the supply of nutrients and humidity in the soil.

CONCLUSION AND RECOMMANDATION

The objective of the study was to assess the effect of Rice Initiative Programme on mean and variance of rice yield under climate variability in Mali. The Rice Initiative Programme was found to have a positive effect on the mean yield of rice. The climate variability was measured by standard precipitation index, temperature deviation from the optimal maximum temperature, and diurnal temperature range. The study found that climate variability affects negatively the mean yield of rice. However, the Rice Initiative Programme and climate variability were not affecting the variance of rice yield. The variability of rice yield was mainly reduced by the use of more organic fertilizer.

The Rice Initiative Programme (RIPRO) should be maintained. The provision of subsidized fertilizer and agricultural extension services (through RIPRO) has been useful since inorganic fertilizer and labour increase the mean rice yield. The government could maintain the fertilizer subsidy programme and engage more agricultural extension agents. Government and its development partners should encourage farmers to increase the application rate of organic fertilizer. The government could also create an enabling environment for local firms to produce organic fertilizer since its high application rate increases rice yield and reduces the rice yield variability. Rice yield was negatively affected by temperature deviation from the optimal maximum temperature (32 °C) for rice and diurnal temperature range. Government and its development partners should encourage farmers to adopt improved rice varieties that withstand high temperature, and early sowing practices to avoid the stresses from high temperatures.

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CONFLICT OF INTEREST

There is no personal or financial conflict of interest between the authors of the article within the scope of the study.

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REFERENCES

AfDB. (2016). *Annual Development Effectiveness Review 2016 Accelerating the pace of change*.

Aker, J. C., Block, S., Ramachandran, V., & Timmer, C. P. (2010). West African experience with the world rice crisis, 2007–2008. *The rice crisis: markets, policies and food security*, 143-162.

Bado, V. B., Djaman, K., & Mel, V. C. (2018). Developing fertilizer recommendations for rice in Sub-Saharan Africa, achievements and opportunities. *Paddy and Water Environment*, *16*(3), 571–586.

https://doi.org/10.1007/s10333-018-0649-8

Barnwal, P., & Kotani, K. (2010). Impact of variation in climatic factors on crop yield: A case of rice crop in Andhra Pradesh, India. *Economics and Management series*, *17*.

Benbi, D. K., & Khosa, M. K. (2014). Effects of temperature, moisture, and chemical composition of organic substrates on C mineralization in soils. *Communications in soil science and plant analysis*, *45*(21), 2734-2753. https://doi.org/10.1080/00103624.2014.950423

Boubacar, I. (2012). The effects of drought on crop yields and yield variability: An economic assessment. *International Journal of Economics and Finance*, *4*(12), 51-60. https://doi.org/10.5539/ijef.v4n12p51

Cabas, J., Weersink, A., & Olale, E. (2010). Crop yield response to economic, site and climatic variables. *Climatic change*, *101*(3-4), 599-616. https://doi.org/10.1007/s10584-009-9754-4

Carew, R., Meng, T., Florkowski, W. J., Smith, R., & Blair, D. (2017). Climate change impacts on hard red spring wheat yield and production risk: evidence from Manitoba, Canada. *Canadian journal of plant science*, *98*(3), 782-795. https://doi.org/10.1139/cjps-2017-0135

Chapagain, A. K., & Hoekstra, A. Y. (2010). *The green, blue and grey water footprint of rice from both a production and consumption perspective*. *Value of Water Research Report Series No. 40*.

Chen, C. C., McCarl, B. A., & Schimmelpfennig, D. E. (2004). Yield variability as influenced by climate: A statistical investigation. *Climatic Change*, *66*(1-2), 239-261. doi:10.1023/B:CLIM.00000 43159.33816.e5.

CPS/SDR. (2013). *Cellule de Planification et de Statistique du Secteur Developpement Rural: Bilan de la campagne agropastorale 2011-2012 et résultats provisoires de la campagne 2012-2013*.

CPS/SDR. (2016). *Cellule de Planification et de Statistique du Secteur Developpement Rural: Resultats definitifs de la campagne agropastorale situation alimentaire et nutritionnelle 2015/2016*.

CPS/SDR. (2017). *Cellule de Planification et de Statistique du Secteur Developpement Rural: Resultats definitifs de la campagne agropastorale situation alimentaire et nutritionnelle 2016/2017*.

Dass, A., Chandra, S., Uphoff, N., Choudhary, A. K., Bhattacharyya, R., & Rana, K. S. (2017). Agronomic fortification of rice grains with secondary and micronutrients under differing crop management and soil moisture regimes in the north Indian Plains. *Paddy and water environment*, *15*(4), 745-760. https://doi.org/10.1007/s10333-017-0588-9

Diakite, L., Diarisso, T., & Drame, Z. (2016). *Etude de la situation de référence du projet commissionné sur le "'Système de Riziculture Intensif (SRI) dans le cadre du WAAAP 2A au Mali.'"*

FAO. (2017). *Mali country fact sheet on food and agriculture policy trends*. *Fao* (Vol. 717).

Fofana, I., Goundan, A., & Domgho, L. V. M. (2014). Impact simulation of ECOWAS rice self-sufficiency policy.

Gujarati, D. N. (2004). *Basic Econometric Methods Fourth Edition* (Prentice H). New York.

Harris, T., & Consulting, T. H. (2014). *Africa agriculture status report 2014: Climate change and smallholder agriculture in Sub-Saharan Africa* (No. BOOK). Alliance for a Green Revolution in Africa (AGRA).

Hollinger, F., & Staatz, J. M. (2015). Agricultural Growth in West Africa. *Market and policy drivers. FAO, African Development Bank, ECOWAS. Pobrano październik*.

Iheonu, C. O., Asongu, S., Emeka, E. T., & Orjiakor, E. C. (2022). *Climate change and agricultural productivity in West Africa* (No. WP/22/065). AGDI Working Paper.

Im, K. S., Pesaran, M. H., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of econometrics*, *115*(1), 53-74.

INSTAT. (2018). *Institut national de la statistique du Mali : Les comptes éconmiques en 2017*.

Izugbara, C., Suubi, K., & Ingabire, M. G. (2024). Gender and adolescent sexual and reproductive health and rights in West and Central Africa: New evidence and emerging gaps. *African Journal of Reproductive Health*, *28*(8s), 15.

Just, R. E., & Pope, R. D. (1978). Stochastic specification of production functions and economic implications. *Journal of econometrics*, *7*(1), 67-86.

Karn, P. K. (2014). *The impact of climate change on rice production in Nepal*. SANDEE.

Kergna, A. O., & Cisse, I. (2014). *Etude sur la chaine de valeur riz en vue d'explorer les facteurs affectant les performances des organisations paysannes (2014).*

Kumar, S., Meena, B. L., Om, H., Kumar, S., & Meena, V. K. (2024). *Understanding Climate Change and Its Impact on Crops*. 12–30. https://doi.org/10.70762/b1c20125

Krishnan, P., Ramakrishnan, B., Reddy, K. R., & Reddy, V. R. (2011). High-temperature effects on rice growth, yield, and grain quality. In *Advances in agronomy* (Vol. 111, pp. 87-206). Academic Press. https://doi.org/10.1016/B978-0-12-387689-8.00004-7

McKee, T. B., Doesken, N. J., & Kleist, J. (1993, January). The relationship of drought frequency and duration to time scales. In *Proceedings of the 8th Conference on Applied Climatology* (Vol. 17, No. 22, pp. 179-183).

Miyamoto, K., Maruyama, A., Haneishi, Y., Matsumoto, S., Tsuboi, T., Asea, G., ... & Kikuchi, M. (2012). NERICA cultivation and its yield determinants: The case of upland rice farmers in Namulonge, Central Uganda. *Journal of Agricultural Science*, *4*(6), 120. https://doi.org/10.5539/jas.v4n6p120

Mohan, S., Simhadrirao, B., & Arumugam, N. (1996). Comparative study of effective rainfall estimation methods for lowland rice. *Water resources management*, *10*(1), 35-44. https://doi.org/10.1007/BF00698810

Okalebo, J. R., Othieno, C. O., Woomer, P. L., Karanja, N. K., Semoka, J. R. M., Bekunda, M. A., … Mukhwana, E. J. (2006). Available technologies to replenish soil fertility in East Africa. *Nutrient Cycling in Agroecosystems*, *76*(2–3), 153–170. https://doi.org/10.1007/s10705-005-7126-7

Paul, J., Choudhary, A. K., Suri, V. K., Sharma, A. K., Kumar, V., & Shobhna. (2014). Bioresource nutrient recycling and its relationship with biofertility indicators of soil health and nutrient dynamics in rice–wheat cropping system. *Communications in soil science and plant analysis*, *45*(7), 912-924. https://doi.org/10.1080/00103624.2013.867051

Paul, J., Choudhary, A. K., Sharma, S., Bohra, M., Dixit, A. K., & Kumar, P. (2016). Potato production through bio-resources: Long-term effects on tuber productivity, quality, carbon sequestration and soil health in temperate Himalayas. *Scientia Horticulturae*, *213*, 152-163. https://doi.org/10.1016/j.scienta.2016.10.022

Poudel, S., & Kotani, K. (2013). Climatic impacts on crop yield and its variability in Nepal: do they vary across seasons and altitudes?. *Climatic change*, *116*(2), 327-355. https://doi.org/10.1007/s10584-012-0491-8

Rahman, M. A., Kang, S., Nagabhatla, N., & Macnee, R. (2017). Impacts of temperature and rainfall variation on rice productivity in major ecosystems of Bangladesh. *Agriculture & Food Security*, *6*(1), 10. https://doi.org/10.1186/s40066-017-0089-5

Rathnayake, W. M. U. K., De Silva, R. P., & Dayawansa, N. D. K. (2016). Assessment of the suitability of temperature and relative humidity for rice cultivation in rainfed lowland paddy fields in Kurunegala district. https://doi.org/10.4038/tar.v27i4.8214

Saha, A., Havenner, A., & Talpaz, H. (1997). Stochastic production function estimation: small sample properties of ML versus FGLS. *Applied Economics*, *29*(4), 459-469. https://doi.org/10.1080/000368497326958

Sarker, M. A. R., Alam, K., & Gow, J. (2012). Exploring the relationship between climate change and rice yield in Bangladesh: An analysis of time series data. *Agricultural Systems*, *112*, 11-16. https://doi.org/10.1016/j.agsy.2012.06.004

Sarker, M. A., Alam, K., & Gow, J. (2013). How Does the Variability in A us Rice Yield Respond to Climate Variables in B angladesh?. *Journal of Agronomy and Crop Science*, *199*(3), 189-194. https://doi.org/10.1111/jac.12011

Styger, E., & Traoré, G. (2018). 50,000 Farmers in 13 Countries: Results from Scaling up the System of Rice Intensification in West Africa.

Van Ypersele de Strihou, J. P. (2014). *Climate Change 2014 Synthesis Report*.

WDR. (2000). *World Development Report 2000 / 1 Attacking Poverty*.

Welch, J. R., Vincent, J. R., Auffhammer, M., Moya, P. F., Dobermann, A., & Dawe, D. (2010). Rice yields in tropical/subtropical Asia exhibit large but opposing sensitivities to minimum and maximum temperatures. *Proceedings of the National Academy of Sciences*, *107*(33), 14562-14567.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.

Wooldridge, J. M. (2013). *Introductory Econometrics: A Modern Approach 5th EDITION* (SOUTH-WEST, Vol. 120–121).

World Resources Institute. (2013). *Creating a Sustainable Food Future : A menu of solutions to sustainably feed more than 9 billion people by 2050. World Resources Report 2013-14*.

Xu, J., Chang, J., Liu, Y., Guo, L., Du, G., & Guan, G. (2025). Impacts of Climate Change on Crops: a comprehensive review. *Hydrological Processes*, *39*(9), e70224.