

# Assessment of Climate Change Impacts on Maize Production in Mali

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## Research

**Keywords:** climate change, food crops, Mali, spatial panel

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# **Assessment of climate change impacts on maize production in Mali**

**Abstract:**

This study examined the total, direct and indirect effects of climatic variables (temperature and rainfall) on crop yields maize in a given region and in neighbouring regions, through a spatial panel analysis of five administrative regions of Mali over a 30-year period (1988 - 2017). Our results show that temperature and rainfall have direct, indirect and total effects on maize yields. In other words, the effect on regions closely linked to the region where the change in temperature or rainfall occurred will be greater than the effect on more remote regions. In addition, the coefficient of variation of precipitation and the interaction between temperature and precipitation as well as the area sown all have negative impacts on maize yields. However, maize yields are negatively correlated with drought. This means that maize production in the local area is declining as a result of increased extreme weather events. Based on these findings, policy makers need to take into account that conditions in the surrounding areas can influence maize yields and that spillover effects differ between crop types. Investments in agricultural research and development should be encouraged to counteract the effects of climate change.

**Key words:** climate change, food crops, Mali, spatial panel

**1. Introduction**

The recent warming of the global average temperature has led to renewed interest in this study. These studies are often carried out on a large scale. And, according to the Intergovernmental Panel on Climate Change, the global average temperature at the earth's surface increased by about 0.8 ° C between 1880 and 2012 (IPCC, 2013). This global warming would exceed 2 ° C on average at the end of the 21<sup>st</sup> century compared to the reference period 1850-1900. More likely increases are still expected in many parts of the world according to IPCC simulation models. On the other

hand, assessing the trend for rainfall is more complex because of the considerable variations between and within countries. Indeed, overall rainfall has tended to decline at least since the 1950s. In particular, West Africa and the tropical rainforest areas have experienced greater variability in rainfall and a resurgence of more intense and widespread droughts (IPCC, 2013).

In recent studies in West Africa, Roudier (2012) uses the M.S.C. approach with the Sarra-H model to assess the impact of climate change on three contrasting varieties of millet and three varieties of sorghum in West Africa. The author finds a "negative evolution of average yield mainly due to the increase in temperatures that rainfall can only mitigate or aggravate". He also finds that this impact is "more negative for short-cycle, constant-cycle varieties than for photoperiod-sensitive varieties". NELSON and al (2009), in their studies of the impact of climate change on agriculture and the costs of adaptation. The results of their studies show that agriculture and human well-being will be negatively affected by climate change. In addition, crop yields will decrease, production will be affected, crop and meat prices will increase and cereal consumption will decline, leading to a reduction in calorie intake and an increase in child malnutrition.

For several decades, Mali, like other countries in the West African region, has been experiencing changes in rainfall patterns. Thus, the drought of 1972 and 1973 was marked as the first major climatic event in the Sahel. These climatic disturbances greatly affected economies as well as ecosystems (CILSS, 2006). According to Wilkinson and al (2015), the case of drought in Mali highlights the complex and dynamic link between climate extremes, poverty and development. Thus Mali is an example of how recurrent droughts can entrench poverty and undermine resilience. Meanwhile, agriculture is a major economic sector in Mali, employing almost 80% of the population and accounting for more than 40% of GDP and 3/4 of exports, and is characterized by low productivity and a lack of modern agricultural technologies (Chauvin and

al. 2012). Despite being an important sector of the national economy, as Mali's agriculture is essentially rain-fed, it is highly dependent on the climate and therefore vulnerable to climate change.

In response to climate change and climate variability, two approaches with economic considerations have often been used in the literature to assess the impacts of climate change on agriculture: the production function or agronomic approach and the Ricardian approach.

The first is an experimental approach that seeks to measure the direct impacts of climate change on different crops. This approach attempts to directly measure the response mechanism of crops to climatic hazards while simulating crop yields using agronomic models. Authors who have adopted this approach include Adams and al (1990), Kane and al (1991), Kaiser and al (1993), Reilly and al (1994), Rosenzweig and Iglesias (1994) and Rosenzweig and Parry (1994), Bassu and al (2014). In Mali, Chaisemartin and al (2010) use scenario simulations to estimate the economic losses that Mali will experience in 2030. They estimate that climate change could lead to losses of about US\$300 million per year (about 15% of the value of agriculture and livestock) under the pessimistic scenario. These losses would be US\$120 million per year (6% of the value of agriculture and livestock) under the optimistic scenario. These results are more alarmist than those previously found by Butt and al (2005) who predict that Mali will suffer economic losses of between US\$ 96 and 116 million. They arrive at this result using projections of climate change induced by greenhouse gas emissions by 2030 and carried out using HADCM and CGCM climate models. Sissoko and al, 2018 adopts the production function approach to assess and compare the resilience of millet, sorghum and maize to climate variability in the regions of Sikasso and Segou. These authors find that the level of resistance of cereals to climate variability differs from one region to another due to the bioclimatic zoning of the study site. For example, cereals are more

related to the climate in the Sikasso region than in the Ségou region. However, these models do not take into account the possibility for farmers to adapt to a new climatic condition (Mendelsohn, 1994).

The second, the Ricardian approach is an alternative to estimates of production functions (Mendelsohn and al. 1994). It takes its name from the theory of the classical economist David Ricardo (1817) that, in a market of pure and perfect competition, ground rent is equal to profit.

Despite the abundant literature on the subject of agriculture and climate change, there are still gaps in the literature to be filled. By using a spatial econometric framework, we take into account the spatial dependence and heterogeneity present in the data, which are not properly accounted for or completely ignored in the previous literature.

Thus, the objective of this study is to assess the impact of climate change on agriculture in Mali. It is therefore a question of assessing the total, direct and indirect effects of rainfall and temperature, floods and droughts on the yields of the main cereal crops in Mali through spatial panel modelling.

## **2. Materials and methods**

### **2.1. Study zone**

Situated between 10 and 25° north latitude, Mali has a dry tropical climate with 65% of its territory in semi-desert and desert conditions. The national territory is currently divided into 10 administrative regions, which are themselves subdivided into circles and communes. The population, estimated at around 20 million inhabitants in 2020, with a growth rate of 3.65% per year, is unevenly distributed over the territory with a high demographic concentration in the southern part of the country.

The country's climate is characterized by the alternation of two seasons:

- A dry season whose duration varies from seven (7) months in the North (November to May) to six (6) months in the South (November to April), characterized by hot and dry winds blowing from the North-East to the South-West, whose duration varies from 6 to 9 months;
- And a wet or wintering season, May to October in the South, June to October in the North with more or less marked inter-seasons corresponding to months "neither rainy nor dry", dominated by humid winds from the Gulf of Guinea (the monsoon), blowing from the South-West to the North-East, bringing rains for 3 to 4 months depending on the zone (National Direction of Meteorology, 2016).

In addition, there are four climatic zones (figure 1):

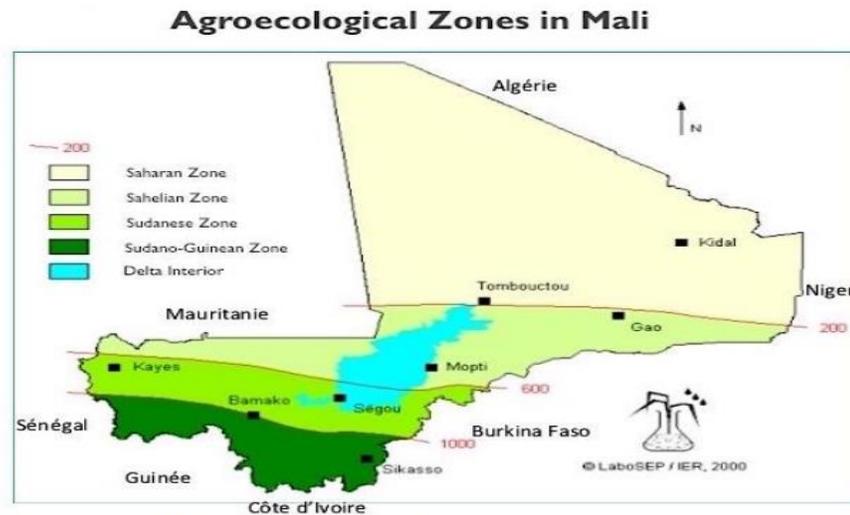


Figure 3. Map of Mali with Principal Agroecological Zones  
Source: Laboratoire Sol-Eau-Plantes de Sotuba / Institut D'économie Rurale (IER), 2000

- Saharan in the north (annual rainfall  $< 200$  mm);
- Sahelian in the center (annual rainfall between 200 mm and 600 mm);
- Sudanese (annual rainfall between 600 mm and 1000 mm) and

- Sudano-Guinean in the south (rainfall > 1000 mm).

Mali's geographical position places it in a Sudano-Sahelian zone that is particularly exposed to climate change, which makes agriculture, the country's main activity, precarious. Changes in climatic conditions, particularly since the droughts of 1970 and 1980, have led to a more arid climate throughout the country, a trend towards an overall decrease in useful rainfall of 20% and a 200 km southward displacement of isohyets, which has greatly weakened the agricultural sector, which is mainly food and rain-fed (DNM, 2018).

To quantify these future impacts due to climate change, projection scenarios have been developed. Thus, the IPCC modelling and the different scenarios developed in the third communication on climate change in Mali. The most plausible climate scenario foresees on average for the horizon 2100 an increase in temperature of 3°C and a decrease in rainfall of 22% compared to normal over the entire territory and an increase in extreme climate events (MEADD, 2018).

## **2.2. Methodology**

### **2.2.1. Sampling**

The data on harvested area (in Hectare, Ha) and crop yields (in Kg / Ha) come from the Conjunction Agricultural Survey (EAC) and are available from the Planning and Statistics Unit of the Rural Development Sector (CPS / SDR) of the Ministry of Agriculture. The data are annual and cover the period from 1988 to 2017. The EAC is a sample survey. It differs from a census in that not all farms are surveyed. It is carried out on a limited number of observation units (farms in rural areas, households in urban areas) selected from the larger set. The data on the sample must be multiplied by extrapolation coefficients in order to obtain data valid for all the regions of Mali.

The crops covered by the survey are essentially cereals (millet, sorghum, rice, maize, fonio, wheat, etc.), cowpea, voandzou, sesame, groundnuts, etc. The data on the sample should be multiplied by extrapolation coefficients in order to obtain data valid for all regions of Mali. This is how we selected the grain maize. In Mali, this cereal has a higher potential yield than other cereals (millet and sorghum), except for rice cultivation.

The climate data come from the database of the National Meteorological Service of Mali (Mali Meteorological). These data include average monthly temperatures and average monthly rainfall for the period 1988 to 2017.

### **2.2.2. Collection of data**

AEC data collection generally consists of: enumerating the holdings in the sample Enumeration Sections (ES) and drawing the 10 sample holdings; enumerating and measuring all plots on the sample holdings and drawing sample plots (1/3) by pure crop type or crop combination; placing yield squares; administering all questionnaires; harvesting the squares and weighing the products from the squares.

### **2.3. Data analysis**

In this paper, the production function approach through spatial panel modelling is adopted to meet our main objective of assessing the impact of climate change on Malian agriculture. The choice of this approach was mainly based on issues related to data availability: more precisely, data were only available on an aggregated basis for the selected crops. In addition, we seek to measure the direct, indirect and total effect of weather conditions on yield without using intermediate variables. In addition, the absence of functional land markets in Mali makes it difficult to determine land values and therefore makes the Ricardian model inapplicable.

The structure of our data guides us towards panel modelling. We estimate above all a standard linear panel data model, i.e. a model without spatial autocorrelation. This model can be used as a reference for the estimation results of spatial panel data models as well as for checking the robustness of these estimation results (Yang and al., 2017). According to Baltagi (2005), Baum and Christopher (2006), the standard linear regression model (SLM) is written:

$$Y_{it} = X_{it}\beta + \alpha_i + \varepsilon_{it} \quad (1)$$

$$\varepsilon_{it} \sim N(0; \sigma_\varepsilon^2)$$

Where  $Y_{it}$  is the variable explained,  $i$  refers to individuals, and  $j$  constitutes the regions<sup>1</sup> (N=5).  $t$  is the dimension of the time series, i.e. 1988 to 2017.  $X_{it}$  is  $1 \times k$  observations of the explanatory variables and  $\beta$  is the  $k \times 1$  vector of indeterminate coefficients.  $\alpha_i$  is an individual effect that cannot be directly observed and quantified and  $\varepsilon_{it}$  is a term of disturbance that varies with the individual and over time. If  $\alpha_i$  is related to  $X_{it}$ , the panel data model model is a fixed-effect model; otherwise it is a random-effect model (Fotheringham and Rogerson, 2008, cited in Guliyevev, 2020).

### 2.3.1. Specification of the spatial panel model

It is important to stress that before any exploratory spatial data analysis (ESDA), it is necessary to specify the spatial links that exist between the elements involved (districts, cities, regions, countries, etc.). Basically, the degree of spatial proximity between geographically located objects is obtained through the representation of a square matrix called a weighting matrix or spatial weighting matrix, noted  $W$ . According to Le Gallo (2002), two main categories can be distinguished of matrix: the adjacency matrices and the generalized weight matrices.

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<sup>1</sup> Mali is divided into ten administrative regions, including five northern regions namely Timbuktu, Gao, Kidal, Taoudéni and Ménaka. Since the security crisis in northern Mali in 2012, most meteorological stations have been sabotaged, leaving a lot of missing data on the series of climatic variables (temperature, precipitation, sunshine, etc.) and therefore we have excluded these northern regions in our analysis.

### Contiguity matrix

To study the interactions between a large numbers of regions, the simple binary contiguity matrix is used, whose components take the value 1 when the regions share a common border and 0 otherwise.

$$w_{ij} = \begin{cases} 1 & \text{if regions } i \text{ and } j \text{ contiguous} \\ 0 & \text{if not} \end{cases}$$

For the same region, there can be no contiguity. In other words, a region is not contiguous to itself. In this case,

$$W_{ij} = 0 \quad \forall i = j$$

To find out the number of regions contiguous to a region  $i$  the elements of the line must be added together.  $i$  of the same contiguity matrix either:

$$L_i = \sum_j^N W_{ij}$$

#### - Generalized weight matrix

$$w_{ij} = \begin{cases} \frac{1}{d_{ij}^\beta} & \text{si } d_{ij} < \bar{d}, i \neq j, \beta > 0 \\ 0 & \text{or } w_{ij} = \begin{cases} \frac{1}{e^{\beta d_{ij}}} & \text{si } d_{ij} < \bar{d}, i \neq j, \beta > 0 \\ 0 & \end{cases} \end{cases}$$

$\beta$  is a distance decay parameter set a priori,  $\bar{d}$  is the threshold value beyond which it is assumed that there is no direct interaction between the region  $i$  and the region  $j$ .

Contiguity matrix and the generalized weight matrices are often standardized s are equal to:

With standardization, the weights are then between 0 and 1 and facilitates the comparison of spatial parameters in spatial processes between models. Harris and al (2011) point out, however, that the concept of distance is itself unclear, so in our study we will use the contiguity matrix.

### **2.3.2. Spatial models**

Building on the seminal spatial econometrics paper by Manski (1993), Elhorst (2010) will establish a series of classifications of the main spatial econometrics models. These spatial models include the Spatial Autoregression Model (SAR), the Spatial Error Model (SEM), the Spatial Autocorrelation Model (SAC) and the Spatial Durbin Model (SDM). In this paper, grain yield was modelled using the Ordinary Least Squares (OLS) method (Standard Linear Regression Model (SLM)) and the principles of Maximum Likelihood (ML), depending on whether or not the spatial argument is included in the analysis.

#### **2.3.2.1. Spatial Autoregression Model (SAR)**

The SAR regression model follows a self-regression process, which is indicated by the presence of a dependency relationship between a set of observations or spatial units (Saputro et al, 2019). Therefore, its formula includes the term spatial shift of the dependent variable. Developed by Anselin and al (2008) then improved by Elhost (2010) in our case, the agricultural production of region  $i$  is explained by the exogenous variables specific to  $i$ , but it is also explained by the exogenous variables of  $i$ 's neighbors. The model is also characterized by the presence of a spatial diffusion effect, this effect is based on the error process, a random is also explained by the exogenous variables of  $i$ 's neighbors. The model is also characterized by the presence of a spatial diffusion effect, this effect is based on the error process, a random shock in region  $i$  disrupts the agricultural production of region  $i$  but also the production of neighboring regions. The model is

presented as an adjustment of the standard panel model with a fixed effect and a random effect, which can be written as follows:

$$Y_{ij} = \sum_{j=1}^N \rho W_{ij} Y_{jt} + X_{it}\beta + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

Where:  $Y_{ij}$  is the agricultural yield of the region  $i$  on the date  $t$ ,  $X_{it}$  represents the matrix of exogenous variables, the set of weights allows to build the weighting matrix  $W_{ij}$ , the value of  $\rho$  reflects the degree of spatial dependence between the units observed (Gelfand and al., 2010), and is between 0 and 1. If  $\rho$  close to 1 close to 1 then the degree of correlation is strong and therefore the agricultural production of the region  $i$  is highly dependent on neighboring observations. Moreover, if  $\rho$  to statistical significance, it demonstrates the existence of a significant spatial dependence between the dependent variables, i.e. agricultural production in a region depends on contiguous regions, that is to say that the agricultural production in a region depends on the contiguous regions,  $\beta$  is the coefficient of spatial self-regression.

$\mu_i$  and  $\lambda_t$  are the individual and temporal effects respectively.

$\varepsilon_{it}$ : the vector of model residuals subject to standard least square assumptions.

### 2.3.2.2. Spatial Error Model (SEM)

In this case, the random  $\varepsilon$  term follows, as in the case of the variable explained in the model with spatial autoregression, a spatial autoregressive process. This model looks like this:

$$Y_{ij} = X_{it}\beta + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

$$\varepsilon_{it} = \sum_{j=1}^N \rho W_{ij} \varepsilon_{jt} + \eta_{it}$$

With  $\rho W_{ij}$ : matrix of spatial autocorrelation effects

$\eta$ : Vector of independent random terms with zero expectation,  $E(\eta) = 0$  and variance  $\sigma^2$ .

### 2.3.2.3. SAC model

We consider a cross-sectional spatial autoregressive model with endogenous variables and spatial autoregressive perturbations (SAC) also called SARAR model, allowing a higher order spatial dependence in the dependent variable, exogenous variables and spatial errors. The model is:

$$Y_{it} = \sum_{j=1}^N \rho W Y_{jt} + X_{it} \beta + \alpha_i + \mu_i + \varepsilon_{it} \quad (4)$$

$$\varepsilon_{it} = \sum_{j=1}^N \delta W \varepsilon_{jt} + \eta_{it}$$

$W Y_{jt}$ ,  $W \varepsilon_{jt}$ , and  $\varepsilon_{jt}$  are  $n \times 1$  spatial shifts for the exogenous variable, the dependent variable and the error terms.  $\rho$ ,  $\alpha_i$ , and  $\mu_i$  are scalar parameters;  $X_{it}$  is an  $n \times 1$  vector of innovations.

### 2.3.2.4. Durbin Spatial Model (SDM)

The SDM includes dependent spatial variables and explanatory variables. It uses the marginal effects of the explanatory variables of neighboring regions / states based on the SAR model. The common specification for SDM is as follows:

$$Y_{it} = \sum_{j=1}^N \rho W Y_{jt} + X_{it} \beta + \sum_{j=1}^N \delta W X_{jt} + \mu_i + \lambda_t + \varepsilon_{it} \quad (5)$$

$Y_{it}$ : The yield of maize cultivation in the region  $i$  at the date  $t$

$\sum_{j=1}^N WY_{jt}$ : The yield of maize cultivation in regions near to  $i$

$X_{it}$  : Represents the explanatory variables of the region  $i$

$\sum_{j=1}^N WX_{jt}$ : The explanatory variables of the neighboring regions to  $i$

$\mu_i + \lambda_t$ : are the individual and temporal effects of the region  $i$  at the moment  $t$

Under the hypothesis  $H_0: \gamma = 0$ , the spatial Durbin model becomes a Spatial Autoregression Model (SAR). Similarly, if  $u = Y - X \cdot \beta$ , we find the SEM model. This model is thus more robust to poor choice of specification even in the presence of spatially auto-correlated errors (SEM)<sup>2</sup>.

Compared to standard linear panel data models, one of the peculiarities of spatial panel data models are their ability to take into account spatial effects, such as spatial dependence and spillover effects (Guliyev, 2020). Another advantage compared to the spatial model based on cross-sectional and temporal data is that the spatial panel data model can capture the individual heterogeneity of spatial units - i.e. individual effects - and can escape missing variables and estimation errors more efficiently (Elhorst, 2014).

Variables and expected signs of the explanatory variables: The study used the following variables and the expected signs of the variables included depending on the nature of the variables used presented in table 1.

<sup>2</sup> LE SAGE et al. 2009.

**Table 1: Description of variables**

<b>Variable</b>	<b>Description</b>
lnRdt	Maize yield in logarithm (Kg/Ha)
lnSup	Maize Area in logarithm (Ha)
lnTemp_moy	Average temperature in logarithm (° C)
lnTemp_sq	Average temperature squared in logarithm (° C)
lnPrec_moy	Average rainfall in logarithm (mm)
lnPrec_sq	Average rainfall squared in logarithm (mm)
lnTemp * Prec	Temperature * Rainfall
lnCVT	Coefficient of Temperature Variation in logarithm
lnCVP	Coefficient of Rainfall Variation in logarithm
Sech	Drought
Flood	Flood

**Source : Author's calculation**

### **Temperature and precipitation data**

The average monthly temperature (Temp\_moy) and average monthly rainfall (Prec\_moy) are based on the growing season for cereals in the regions of Mali (June to October). We consider that rainfall and off-season temperatures would not affect cereal production. The monthly average temperature and the monthly average rainfall value reflect inter-seasonal variability.

### **Data on the seasonal variation coefficient of the temperature and of art rainfall**

The coefficient of seasonal variation of the temperature (CVT) and seasonal variation of rainfall (CVP), captures seasonal variability s temperature and precipitation and taken as seasonal ratio the standard deviation to the mean of the temperature and rainfall, respectfully.

### **Floods and droughts data**

Thanks to the SPI (Standardized Precipitation Index), it is possible to identify periods of drought and flooding (Blanc, 2012). In this study, droughts and floods begin when the SPI reaches

values of  $-1.5$  and  $+1.5$ , respectively, and end when the index returns to a positive and negative value, respectively.

Excel 2010, GeoDa and STATA 14 software are used in data analysis.

### 3. Results and discussion

Table 2 presents the descriptive statistics (mean (Mean), standard error (St.Dev), minimum (Min) and maximum (Max)) of the study variables.

Thus, the average maize yield value (Kg/Ha) is 1276.84 with a volatility of 607.36 (Kg/Ha). In addition, the minimum and maximum values of maize yield (Kg/Ha) are 377 and 3006.97 respectively.

The average temperature fluctuates between 26.2 and 31.53°C. The coefficient of temperature variation has a standard deviation of 0.014 mm, which indicates that there is little year-to-year seasonal variation in temperature.

As far as precipitation is concerned, the seasonal average value is 134.61 mm. It varies between 45.92 and 252.62 mm with a variability of 44.01 mm. The coefficient of variation of precipitation has an average of 0.570 mm and the minimum and maximum values are between 0.23 and 1.04.

**Table 2: Descriptive statistics of the control variables**

<b>Variable</b>	<b>Mean</b>	<b>St. Dev.</b>	<b>Min</b>	<b>Max</b>
Rdt	1276,849	607.3619	377	3006,972
Sup	57513.65	77567.95	4	446832
Temp_avg	28.76	1.51	26.2	31.53
Prec_moy	134.61	44.01	45.92	252.62
CVT	.0483559	.0149194	.0239784	.1081346
CVP	.5705424	.1661198	.2316991	1.049772

**Source: Author's calculation, data from CPS / Agricultural and Mali-Meteorological**

### 3.1. Spatial dependency test

Standard linear panel data models assume that there is no cross-sectional correlation between observation units. Ignoring potential cross-sectional dependence can produce biased estimates (Le Sage and Pace, 2009).

The interactions between administrative regions in Mali suggest that spatial spillovers may lead to a cross-dependency of maize yields between these regions.

Figure 1 shows the distribution of average yields over the period 1988-2017: different colors identify the quartiles of the distribution, with darker areas corresponding to higher average yields.

The average maize yields are concentrated in the Sikasso region, while the Mopti particular has relatively lower average yields.

To formally test the cross-sectional dependence, we will estimate the linear fixed effect (FE) panel model and the random effect (RE) model and then carry out the CD test of Pesaran (2004) to account for the existence of a possible cross-sectional dependence. The results of the standard panel model are reported in Table 3.

**Table 3. Panel data model results without spatial effects**

Variables	Pooled OLS	Fixed effects	Random effects
lnSup	0.139 *** (0.042)	-0.137 * (0.073)	0.139 *** (.045)
lnTemp_moy	5.110 ** (2.003)	6.794 *** (2.294)	5.110 ** (2.272)
lnTemp_sq	-0.090 *** (0.035)	-0.121 *** (0.039)	-.089 *** (.040)
lnPrec_moy	2,379 (1,930)	0.243 (2.079)	2.379 ** (.963)

lnPrec_sq	-0.107 (0.100)	-0.018 (0.108)	-0.107 ** (.047)
lnTemp * Prec	.018 (.128)	.0127 (.043)	.019 (.086)
lnCVT	0.027 (4.519)	-1.589 (4.826)	0.027 (5.528)
lnCVP	0.008 (0.372)	0.310 (0.365)	0.008 (.311)
Sech	-0.352 (0.242)	-0.048 (0.236)	-.350 (.284)
Flood	-0.152 (0.220)	-0.359 (0.233)	-0.152 (.119)
Constant	-79,597 ***	-87,176 ***	-79,597 ***
Observation	150	150	150
R <sup>2</sup> _within		.6636	

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Hausman Test, Chi2 (10) = 27.74, Prob> chi2 = 0.0020  
Peseran-CD test stat = 5.794, Pr = 0.0000  
Average absolute value of the off-diagonal elements = 0.340

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Standard errors in parentheses. \* p <0.10, \*\* p <0.05, \*\*\* p <0.01

In panel modelling, the choice of models is guided by tests. The Hausman test allows to arbitrate between a fixed effect model and a random effect model. And, according to the Hausman test, the hypothesis of the random effect model is strongly rejected (Prob>chi2= 0.0020<0.05). As we can also see, the CD test strongly rejects the null hypothesis of cross-sectional non-dependence (Pr = 0.0000). Moreover, the mean absolute value of the off-diagonal elements of the cross-correlation matrix of the residuals is 0.340, which indicates a possible cross-sectional dependence (De Hoyos and Sarafidis, 2006). Therefore, there is sufficient evidence to suggest the presence of cross-sectional dependence under a fixed-effect (FE) specification.

To summarize, we controlled for fixed effects in the following spatial regression models.

### 3.2. Statistical criteria for model choice

According to Le Gallo (2002), different approaches can be used to choose the most appropriate model. We have chosen the so-called mixed approach which consists in starting with

the bottom-up approach (non-spatial model) but, in case of spatial interaction ( $\rho \neq 0$  or  $\lambda \neq 0$ ) instead of choosing directly a SAR or SEM model, to propose to use the Spatial Durbin Model (SDM). Lagrange multiplier tests (LR test) and likelihood ratio tests (Wald test) make it possible to select between the SAR, SEM or SDM model (Elhorst, 2010).

The SDM model estimation highlights the spatially autoregressive coefficients ( $\rho$ ) negative and significant at the 1% threshold. Maize yields are therefore spatially autocorrelated as indicated by the value -0.2370 taken by  $\rho$  and significant at the 1% threshold (Table 4). This result reflects the diffusion effect between regions located close to each other.

In order to highlight the direct and indirect effects, we can carry out Wald and likelihood ratio (LR) tests in order to select the most appropriate model. Regarding the selection of the model, in the  $H_0$  test:  $\theta = 0$  using Wald tests (17.70, with  $\chi^2(8)$  degree of freedom,  $p=0.0388$ ) and LR test (20.34, with with  $\chi^2(8)$  degree of freedom,  $p=0.0091$ ), indicates that the assumption of whether the SAR model can be used to estimate the SDM model is still rejected (Table 4). By analogy, the assumption that the MDS model can be simplified to the SEM model is rejected (Wald test= 15.35, with  $\chi^2(8)$  degree of freedom  $p=0.0817$ ; LR test=23.31,  $\chi^2(8)$  degree of freedom,  $p = 0.0030$ ). Given this consistent evidence, and considering that spatially shifted variables also control for omitted relevant variables, we focus on SDM.

However, the interpretation of the coefficients of the spatial models remains delicate. They can only be interpreted in the same way as in classical econometrics because of the spatial interaction between economic agents. Instead, LeSage and Pace (2009) propose to estimate the direct, indirect and total effects of the determinants.

**Table 4: Results of panel data models with spatial effects on maize yield**

Variable	SDM		
	Coefficient	t-statistics	p-Value
lnSup	-. 15060	.0640	0.019
lnTemp_moy	5.5909	2.3478	0.017
lnTemp_sq	- .0992	.0407	0.015
lnPrec_moy	- .3593	1.6134	0.824
lnPrec_sq	.1162	.3332	0.727
lnTemp * Prec	-.1047	.00019	0.068
lnCVT	- 6.056	3,613	0.094
lnCVP	.3792	.3048	0.214
Sech	- .2326	. 1844	0.207
Flood	- .1002	. 1884	0.595
W * lnSup	- .09173	.04179	0.028
W * lnTemp_moy	5.6395	1,887	0.003
W * lnTemp_sq	- .0971	.0329	0.003
W * lnPrec_moy	- 4.7048	2.6446	0.075
lnPrec_sq	1.0633	.5625	0.059
W * lnTemp * Prec	- .1047	.00019	0.068
W * lnCVT	- .1.9412	3.5213	0.581
W * lnCVP	.3784	.2812	0.178
W * Sech	-. 1865	.4529	0.680
W * Flood	.2147	.1750	0.220
$\rho$	-. 2370	.04844	0.000
$\sigma^2$	.1314	.0277	0.000

Wald test spatial lag 17.70 (**p = 0.0388**)

LR test spatial lag 20.34 (**p = 0.0091**)

Wald test spatial error 15.35 (**p = 0.0817**)

LR test spatial error 23.31 (**p = 0.0030**)

Observation 150

Log Likelihood -103.5653

**Source: Author's calculation, data from CPS / Agricultural and Mali-Meteorological**

### 3.3. Analysis of spatial effects

In order to further investigate the possible sources of impact, we calculate direct, indirect and total effects. The average direct, indirect and total effects of our explanatory variables are presented in Table 6.

Based on the direct effects, the results show that average seasonal temperature and rainfall have a positive and significant impact on maize yields. In other words, a 1% increase in temperature and precipitation would lead, all other things being equal, to an average increase of 4.84% and 0.20% respectively in maize yields in the local region and neighbouring regions. This can be explained by the fact that the plants need heat for photosynthesis and moisture until the ripening phase. Above a certain threshold, these two variables become harmful. While the area sown and the interaction between temperature and rainfall are negatively and significantly correlated with maize yields.

Based on indirect effects, the temperature is equal to 4.17 (prob<0.05), indicating that a 1% increase in temperature in neighbouring regions would result in a positive 4.2% change in maize yields in the local area. However, the indirect effect of the precipitation variable is negative and significant at the 1% threshold. In other words, a 1% increase in rainfall in all other regions would decrease the maize yield in a typical region by 0.03%. In the same vein, the indirect effects of the drought variable (Sech), we note that the elasticity of the explanatory variable (Sech) is negative and significant at the expected sign. As for the inter-seasonal variation in rainfall (CVP), it is significant at the level of 5% and negatively related to the effects of maize. However, an increase in seasonal rainfall variability (lnCVP) of 1% from one season to the next in the region would reduce maize yields by about 0.62% of a kilogram per hectare in all other neighbouring regions. This indirect impact takes into account the fact that the inter-seasonal variation in rainfall (lnCVP) has a negative impact on yields in other regions, which in turn negatively influences yields in our

typical region due to the presence of a positive spatial dependence on yields in neighbouring regions.

We also find that the direct and total effect of temperature and precipitation are significantly positive. An increase in temperature or precipitation will significantly increase maize yield in the local area and subsequently increase maize yield in all neighbouring areas. In other words, a 1% increase in temperature would result in an increase in maize yields in the local region of 4.84% and regional yields of 9.01%. In addition, a 1% increase in rainfall would increase maize yields in the local region by 0.20% and regional yields by 4.01%. This is sufficient evidence that temperature and rainfall are beneficial for maize production up to a certain threshold, above which temperature and rainfall can have adverse effects on average maize yields. Second, the variable coefficient of variation in rainfall (lnCVP) has the expected positive effect, while the area planted and the interaction between temperature and rainfall have a negative impact on maize yields. In addition, intra-seasonal temperature variability has a considerable total effect on maize yield.

**Table 6: Estimates of direct, indirect and total effects on maize yield**

Variable	SDM		
	Total Coefficient (t-Value)	Direct Coefficient (t-Value)	Indirect Coefficient (t-Value)
lnSup	-.1952 *** (0.003)	-.1435 ** (0.029)	-.0516 (0.208)
lnTemp_moy	9.018 *** (0.000)	4.8468 * (0.057)	4.1713 ** (0.033)
lnTemp_sq	-.1576 *** (0.000)	-.08656 * (0.051)	-.07113 ** (0.039)
lnPrec_moy	4.0123 * (0.099)	.1982 ** (0.047)	-.02586 *** (0.008)
lnPrec_sq	.9384 * (0.069)	-1411 (0.694)	1.0795 * (0.056)
lnTemp * Prec	-.0716 *** (0.002)	-.1047 * (0.068)	-.29461 (0.324)

lnCVT	-6.3786 (0.014)	-5.7215 (0.135)	-6.3786 (0.114)
lnCVP	.62035 * (0.073)	.3098 (0.344)	.6203 * (0.073)
Sech	-.3714 (0.375)	-.2108 (0.269)	-.24622 *** (0.017)
Flood	.1042 0.652	-.1404 (0.450)	-.3713 (0.375)

**Source : Author's calculation**

Associated probability in parentheses

\* p <0.10, \*\* p <0.05, \*\*\* p <0.01

#### 4. Conclusion and policy implications

This paper assessed the impacts of climate change on maize crop yields. The aim was to assess the total, direct and indirect effects of rainfall and temperature, floods, droughts and coefficients of variation of temperature and rainfall on maize yields through spatial panel modelling to account more effectively for spatial autocorrelation. To do this, we used panel data from five regions of Mali (excluding the northern regions of Timbuktu, Gao, Kidal, Ménaka and Taoudéni) over the period 1988 to 2017.

Pesaran's (2006) cross-sectional dependency test was carried out even before comparing spatial panel models in order to take into account the spatial interactions that may exist between regional units. We thus found a transversal dependence between regions. We test spatial models (spatial autoregressive models (SAR), spatial error models (SEM) and spatial durbin models (SDM) using the Wald and LR tests that capture spatial effects. These tests guide us in selecting the appropriate specification and the one that appears to be best suited to our data. Thus, the most appropriate and consistent was the SDM (Spatial Durbin Model) among the spatial panel data models provided for interpretation.

We then estimate our SDM model by looking at spatial spillovers (the effects of changes in independent variables on the dependent variable). As suggested by Pace and Le Sage (2006), the effects of the independent variables were divided into total, indirect (spatial spillover effects) and direct effects in order to improve the identification of the actual impacts and spatial interactions of the factor components on average maize yields.

Following the regression results, it can be seen that the mean total impacts of temperature and mean seasonal rainfall have positive and significant effects on mean maize yields, while the interaction between temperature and rainfall has negative and significant effects on mean maize yields, and the drought variable is negatively and significantly correlated with maize yields at the 10% threshold.

Average direct impacts, temperature and average seasonal rainfall have direct positive and significant effects on maize yields, while the area planted and the interaction between temperature and rainfall have direct negative and significant effects on maize yields. In other words, a 1% increase in temperature and rainfall leads to a positive variation of 4.84% and 0.20% respectively on maize yields in the local area and neighbouring regions. Based on average indirect impacts, temperature has positive effects on maize yields in neighbouring regions. In other words, a 1% increase in temperature leads to a positive 4.2% change in maize yields in neighbouring regions. However, the effect of rainfall is negative and significant at the 1% threshold. In other words, a 1% increase in rainfall would decrease maize yields in neighbouring regions by 0.03%. In addition, the direct, indirect and total effects of the precipitation variable are significantly positive. Overall, our results indicate that when assessing the impacts of climate change on maize crop yields in Mali, policy makers need to take into account that conditions in surrounding areas can influence cereal crop yields and that the effects of spillover effects differ between crop types.

From a political point of view, two main recommendations can be made. On the one hand, the use of drought-tolerant seeds should be promoted in order to reduce the expected adverse effects of climate change and climate variability. On the other hand, the adoption of any policy to improve maize production in regions with rainfall deficits or high temperature increases must not only take into consideration the amount of water available in the local area's dams and water tables, but also intensify irrigation practices that can be a good policy for mitigating climate change externalities collectively and regionally.

## **List of abbreviations**

**CPS: Rural Development Sector**

**CVT: Coefficient of seasonal Variation of the Temperature**

**CVP: Coefficient seasonal Variation of rainfall**

**EAC: Conjuncture Agricultural Survey**

**ES: Enumeration Sections**

**ESDA: Exploratory Spatial Data Analysis**

**GES : Gaz à Effet de Serre**

**IER: Institute of Rural Economy**

**MEADD : Ministère de l'Environnement, de l'Assainissement et du Développement Durable**

**ML: Maximum Likelihood**

**OLS: Ordinary Least Squares (OLS)**

**SAC: Spatial Autocorrelation Model**

**SAR: Spatial Autoregression Model**

**SDM: Spatial Durbin Model**

**SEM: Spatial Error Model**

**SLM: Standard Linear regression Model**

**SPI: Standardized Precipitation Index**

#### **4.1. Declaration of data availability**

The datasets used during the current article are available from the corresponding author on request.

#### **4.2. Declaration of interest statement**

The authors declare no potential conflict of interest.

#### **\*\*3. Funding**

I have no funding to be able to pay the processing costs of my article that I want to publish in your International Journal of Climate Change Strategies and Management

#### **\*\*4. Authors' contributions**

The first contribution is, the study that we propose is original insofar as there is no previous work borrowing such a procedure on this theme applied in Mali.

#### **5. Authors' information (optional)**

'Not applicable' for that section.

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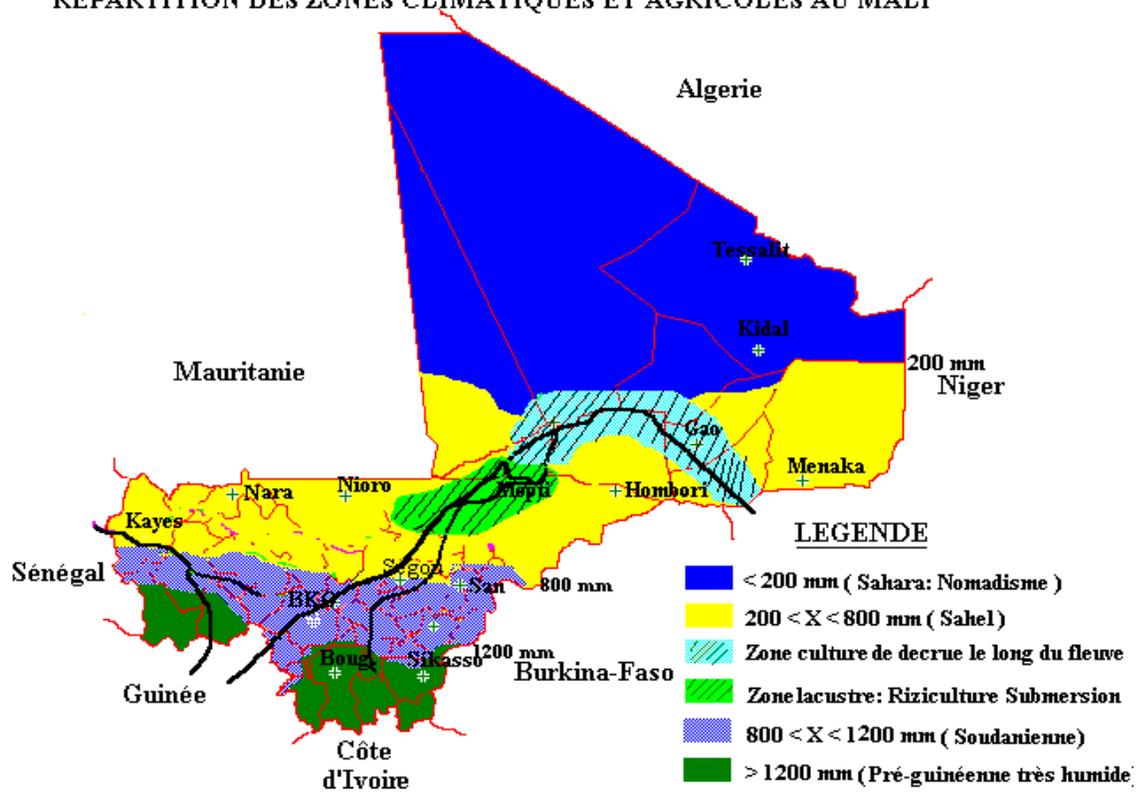
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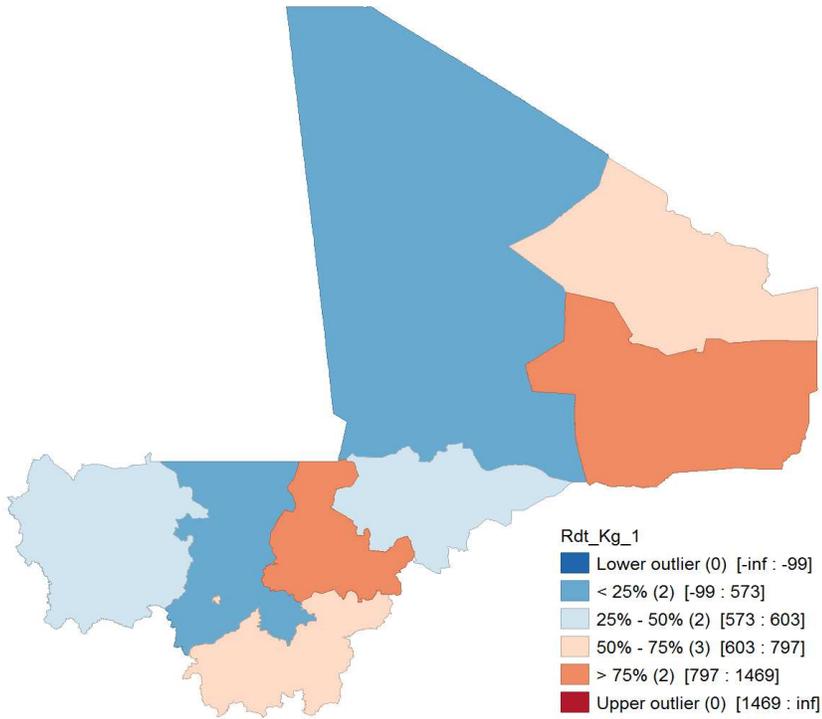
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**Figure 1: geographical location and climatic zones of Mali (source DNM)**

## REPARTITION DES ZONES CLIMATIQUES ET AGRICOLES AU MALI



**Figure 2: Distribution of average yields (Kg/hectare) between 1988 to 2017**



**Source: Author's calculation**

# Figures

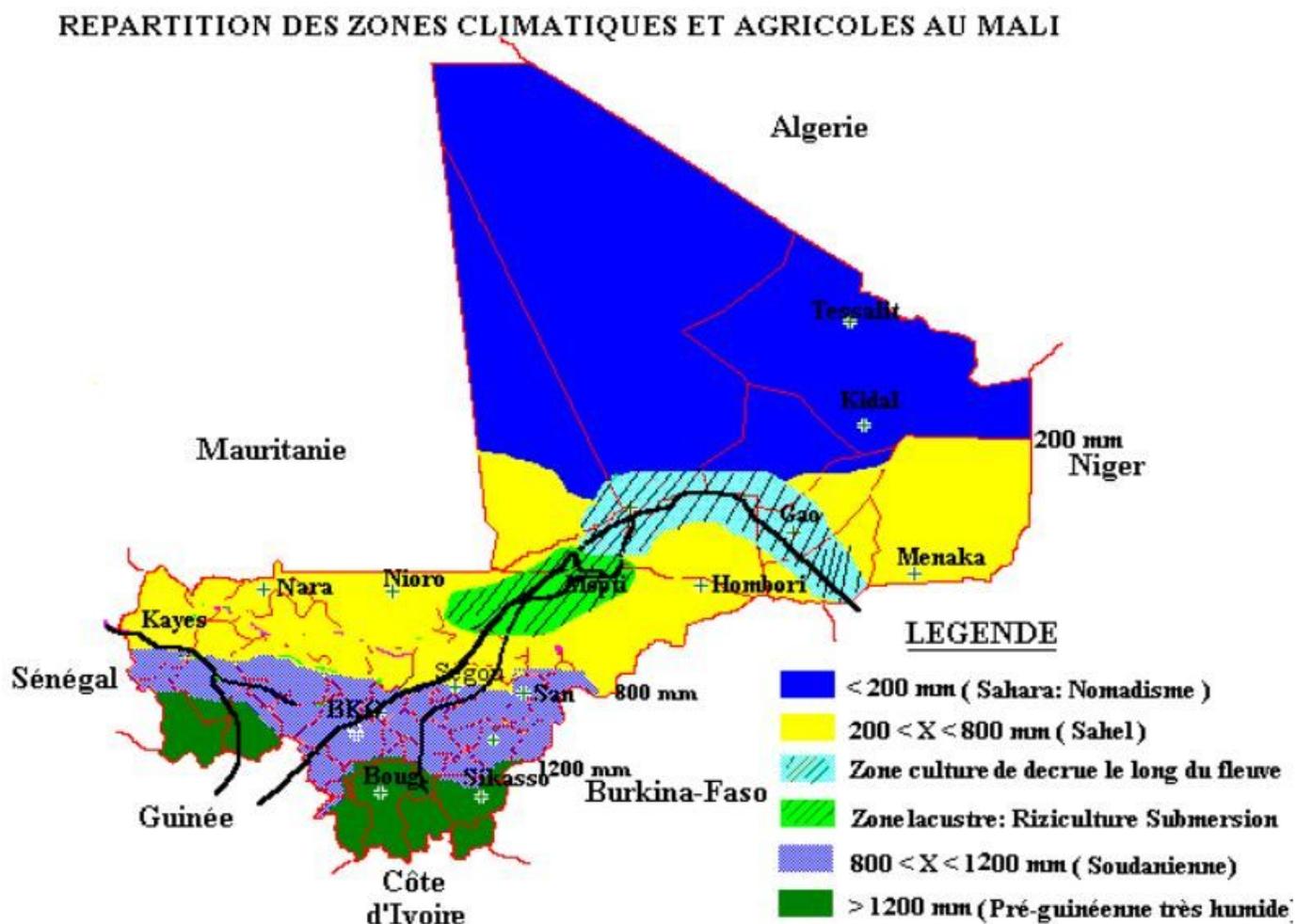
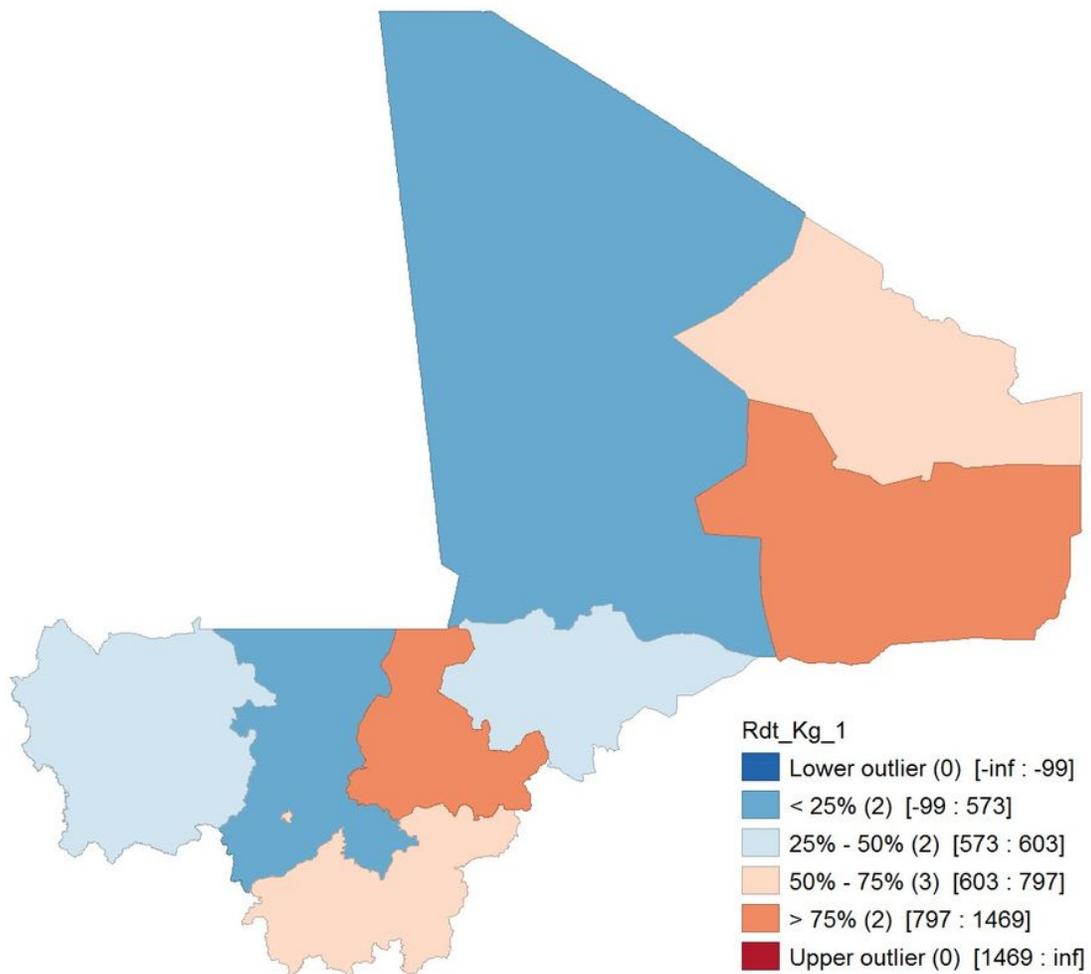


Figure 1

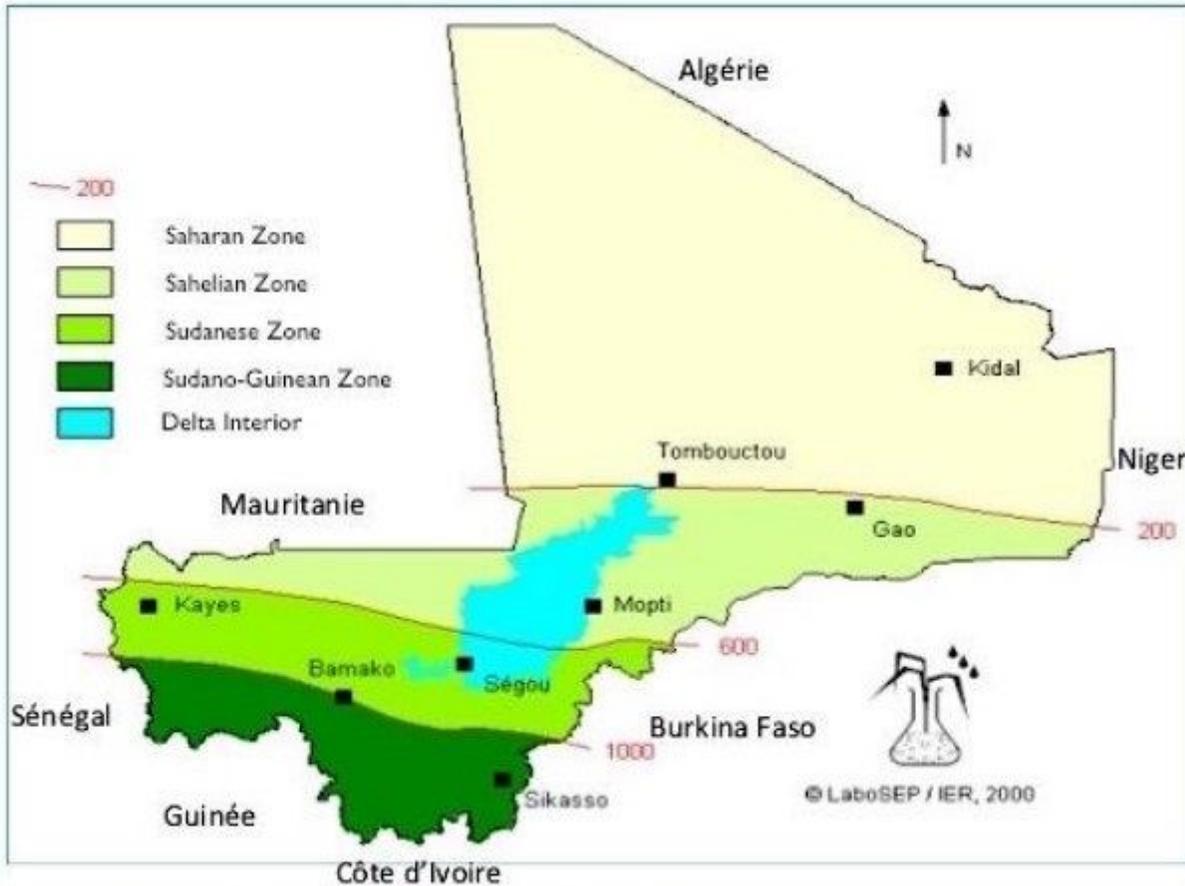
geographical location and climatic zones of Mali (source DNM) Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.



**Figure 2**

Distribution of average yields (Kg/hectare) between 1988 to 2017 Source: Author's calculation. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

## Agroecological Zones in Mali



**Figure 3**

Map of Mali with Principal Agroecological Zones Source: Laboratoire Sal-Eau-Plantes de Sotuba / Institute D'economie Rurale (IER), 2000 Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.