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Spatial variability in agricultural yield responses to climate change: Implications for index insurance in Burkina Faso

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Abstract

Index-based insurance has emerged as a compelling strategy for agricultural risk management in Africa, particularly in contexts where smallholder farmers are disproportionately exposed to climate-related hazards. Despite its potential, the effectiveness of this mechanism is often constrained by the spatial heterogeneity of crop yield responses to climatic variables – an issue that significantly contributes to basis risk. This study investigates the value added by spatial econometric approaches, with a focus on the geographically weighted panel regression (GWPR) model, in enhancing the calibration of index-based insurance schemes under conditions of spatial instability in the relationship between maize yields and climate indicators in Burkina Faso. Drawing on panel data from eight meteorological stations spanning the period 1995 to 2009, the empirical analysis reveals a notable reduction in basis risk – estimated at 31.84% – when the GWPR model is applied. These results highlight the methodological relevance of GWPR for designing more context-sensitive and spatially adaptive insurance instruments, thereby offering a pathway toward more effective and equitable agricultural risk mitigation strategies in sub-Saharan Africa.

Key words: GWPR, spatial heterogeneity, geographic basis risk, weather index insurance, risk-pooling

1. Introduction

Agriculture in sub-Saharan Africa is heavily dependent on rainfall, rendering it acutely susceptible to climatic variability. To mitigate this vulnerability, index-based agricultural insurance (IBAI) has emerged as a key risk-management tool aimed at shielding smallholder farmers from losses associated with extreme weather events (Hazell & Hess 2010). Unlike conventional indemnity insurance, IBAI activates payouts based on remotely sensed indicators – such as precipitation or temperature indices – rather than actual losses. While this approach offers several operational advantages, it is hindered by a critical limitation: basis risk, defined as the mismatch between insured losses and the index-triggered payouts.

Geographically weighted panel regression (GWPR) offers a promising methodological solution to this issue by explicitly accounting for spatial heterogeneity in the relationships between agroclimatic variables and agricultural performance. Spatial variation in crop yields poses a significant obstacle in the design of reliable index-based insurance products, as it directly influences the accuracy of payout indices (Barnett & Mahul 2007). This inherent risk compromises both the effectiveness and appeal of such products, especially in developing regions, where farming systems are highly sensitive to climatic shocks (Giné & Yang 2009). In line with this, Carter and Janzen (2018) underscore the challenge of constructing indices that are spatially precise enough to offer meaningful protection. Clarke (2016) further advocates for index structures that incorporate spatial variability as a means of reducing basis risk and ensuring contract sustainability.

Empirically, Brunsdon *et al*. (1996) demonstrate that the capacity of the geographically weighted panel regression (GWPR) model to capture localised spatial effects enables insurers to fine-tune pricing and claims strategies in alignment with regional characteristics. Similarly, Anselin (2005) highlights the utility of spatial econometric models in capturing spatial dependencies, thereby enhancing risk assessment and the accuracy of payouts at finer geographic scales.

This study aims to show that the GWPR model offers superior capacity to model the relationship between maize yields and climatic variables, thereby serving as a robust methodological foundation for the development of index-based insurance schemes that are responsive to local conditions in developing countries. To this end, the study evaluates the GWPR model against alternative approaches that incorporate varying degrees of spatial heterogeneity in the yield–climate relationship.

The remainder of this article is organised as follows: Section 2 contextualises and justifies the research; Section 3 details the data and methodological framework; Section 4 presents and discusses the results; and Section 5 concludes the paper.

2. Status of agricultural insurance in Burkina Faso

Since the late 2000s, a growing number of initiatives across sub-Saharan Africa have sought to develop index-based insurance schemes grounded in climate variables such as rainfall and temperature. Currently, the World Bank is spearheading approximately 10 projects spanning around 20 countries to support the expansion of this insurance model. A principal advantage of index insurance lies in its reliance on objectively, observable climatic indices, which are resistant to manipulation by stakeholders. By decoupling insurance payouts from actual individual yields, and instead linking them to predetermined climatic thresholds, this approach eliminates the need for costly field assessments and significantly reduces administrative expenses.

Moreover, the structure of climate index-based insurance reduces vulnerability to fraud and moral hazard. Nonetheless, challenges persist, particularly regarding spatial misalignment**,** where insurance design fails to adequately reflect local agroclimatic conditions (Sarris *et al*. 2006). This issue is particularly pronounced in the Sudano-Sahelian regions, where rainfall exhibits exceptionally high spatiotemporal variability, significantly constraining agricultural productivity (Müller *et al*. 2012).

2.1 Weather index insurance

Index-based agricultural insurance presents a promising strategy for managing climate-related risks faced by small-scale farmers in developing countries. Its appeal lies in its simplicity, low administrative costs, and ability to mitigate information asymmetries such as adverse selection and moral hazard (Fuchs Tarlovsky & Wolff 2011). Unlike conventional insurance, payouts are triggered when a predefined weather index (e.g. rainfall) crosses critical thresholds, rather than by assessing actual losses.

However, the effectiveness of such insurance is constrained by basis risk – the discrepancy between real losses and payouts determined by the index. This can result in under-compensation for severely affected farmers and over-compensation for others. The extent of basis risk depends on factors such as index quality, geographic scale, and the nature of the shocks (Barré *et al*. 2016). It includes both idiosyncratic and covariate components, with the latter being more prevalent and impactful in sub-Saharan Africa (Udry 1990).

Since local risk-sharing is ineffective against widespread (covariate) shocks, formal insurance mechanisms are necessary. Consequently, index insurance schemes must be carefully designed to reflect the spatial heterogeneity of agricultural zones and to align closely with meteorological station data to reduce basis risk and enhance effectiveness.

2.2 Study area: Agricultural regions of Burkina Faso

Burkina Faso, located at the intersection of both humid and arid zones in West Africa, is defined by three major climatic regions. The southern Sudanese zone receives annual rainfall ranging from 900 to 1 200 millimetres, while the central, sub-Sahelian zone experiences precipitation between 600 and 900 millimetres annually. In the northern Sahelian zone, rainfall declines further to a range from 400 to 600 millimetres per year. Like much of West Africa, Burkina Faso has been experiencing a persistent rainfall deficit since the early 1970s (Mahé & Paturel 2009), which mirrors a broader decline in precipitation levels observed between 1896 and 2006. This sustained reduction in rainfall presents significant socio-economic challenges, particularly as the nation's primary economic sectors – agriculture and livestock farming – are highly dependent on seasonal precipitation. Consequently, each rainfall deficit leads to reduced agricultural output and heightens food insecurity. A notable aspect of this decline in rainfall is the decrease in the number of rainy days, which further exacerbates issues of water availability and agricultural productivity (Le Barbé & Lebel 1997).

In many developing countries, including Burkina Faso, agricultural practices often fail to achieve optimal productivity, falling short of the potential yields that could be realised under prevailing climatic conditions. Administratively, Burkina Faso is divided into 13 regions, with meteorological stations situated in eight of these regions (see Table 1). The country follows a bimodal seasonal cycle, with a rainy season from May to September and a dry season from October to April.

Table 1: Regional statistics

Provinces	Average 10-day rainfall (mm)	Number of rainy days (average 10 days)	Average temperature (degrees Celsius)	Corn yield (t/ha)
Centre	42.55	3.90	28.92	0.86
Centre-Sud	59.90	4.40	27.27	1.13
Est	49.82	4.05	28.17	1.14
Hauts-Bassins	57.24	4.80	26.72	1.79
Mouhoun	48.16	4.05	28.62	1.43
Nord	42.43	3.38	29.71	0.77
Sahel	30.94	2.91	31.14	0.56
Sud-Ouest	57.17	4.05	27.08	1.47

Note: Compiled by author using data from the National Meteorological Agency of Burkina Faso

The variability in maize yields across the different regions exhibits a significant degree of heterogeneity. Specifically, the Sud-Ouest, Hauts-Bassins and the majority of the Centre-Sud regions are situated within the Sudanese climatic zone. In contrast, the Mouhoun, Est and Centre regions are classified within the sub-Sahelian zone, while the Nord and Sahel regions fall within the Sahelian zone. Empirical observations indicate that maize yields generally tend to be higher in regions characterised by greater availability of water resources.

2.3 Agricultural insurance in Burkina Faso

Launched in 2011 through the collaboration of various international partners – including the Global Index Insurance Facility (GIIF), the Africa Enterprise Challenge Fund (AECF), Allianz for a Green Revolution in Africa (AGRA), as well as organisations such as CIRAD, Oxfam, Swiss Re and EARS – the "Sahel Crop Insurance" initiative has developed two primary products: drought insurance for maize producers and yield insurance for cotton producers. This initiative operates through eight distribution networks and provides coverage to more than 250 villages.

Initially, the index insurance employed the relative evapotranspiration index from 2011 to 2014, before transitioning to an estimated satellite-derived rainfall index, starting with the 2015/2016 campaign. The insured crops include maize, millet and peanuts, with coverage structured around three key growth phases: germination (40 days), flowering (30 days), and maturation (30 days). Maize represents over 86% of the demand for Sahel Crop Insurance coverage (William *et al*. 2016), which justifies the focus of this study on this particular crop. However, incorporating other crops in future research is essential to expand the demand for insurance products across a broader range of agricultural commodities. The scheme guarantees 75% of the total insured amount during the germination phase and 100% during the flowering and maturation phases. Premium rates vary regionally, ranging from 7.75% to 11.5% of the insured sum.

The insurance scheme establishes a "trigger" threshold – representing the rainfall level below which compensation is activated – and an "exit" threshold, corresponding to the level at which maximum compensation is payable. Compensation is calculated proportionally between these thresholds: no payout occurs if accumulated precipitation exceeds the trigger level. If it falls below, the scheme provides a linear payout, with a fixed amount for each millimetre of rainfall below the upper threshold until reaching the exit threshold. If rainfall drops below this exit threshold, the maximum fixed compensation is paid. The total payments across the three growth phases are capped at the insured amount.

Since its inception, the number of subscribers declined over the initial three years, decreasing from 534 in 2012 to 378 in 2013, and further to 289 in 2014 (OXFAM 2016).

The geographic area covered by index insurance is divided into four main areas: zone 1 (R1) is characterised by relatively abundant rainfall; the index insurance premium is 7.75% of the total guaranteed amount. Zone 2 (R2 and R3) is also well watered, and the insurance premium is 9.30% of the total guaranteed amount. Zone 3 (R4 and R5), located in the Sudano-Sahelian climatic zone, is quite heterogeneous in terms of precipitation, and the insurance premium is 10.80%. Finally, zone 4 (R6) is relatively less watered than the other three, with an insurance premium of 11.50% of the total guaranteed amount (see Figure 1 for the zones). The mismatch between estimates and observations is seen as the main discouraging factor for index insurance adherence (OXFAM 2016).

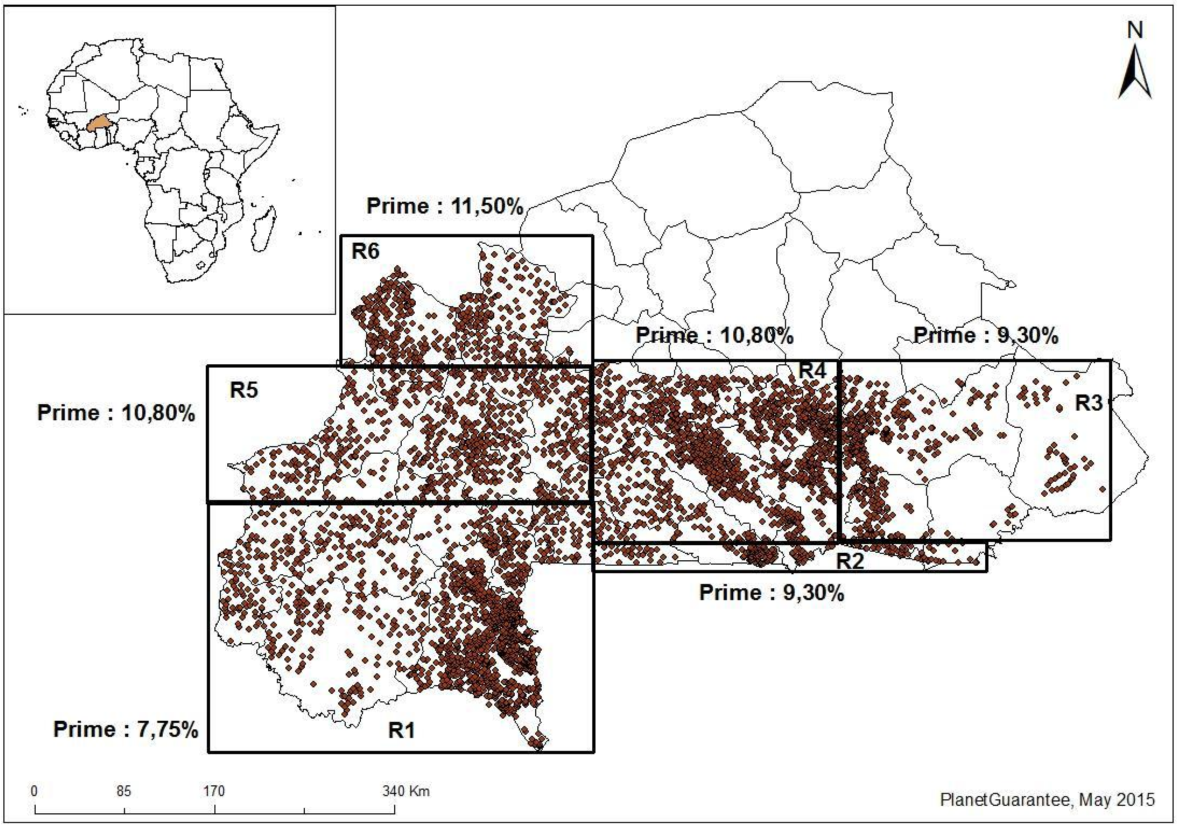

Figure 1: Spatial pricing of index insurance in Burkina Faso

2.4 Application of GWPR in African Index Insurance Systems

Several studies in Africa have incorporated the geographically weighted panel regression (GWPR) model to capture spatially varying sensitivities of crop yields to climate factors. Dinku *et al*. (2010) used GWPR to analyse the correlation between satellite-derived rainfall data and crop yield in Ethiopia, revealing substantial local variation. This allowed for the localised design of weather indices, thereby improving the targeting of payouts. Similarly, Greatrex *et al*. (2015), in collaboration with the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS), emphasise the potential of using spatially adaptive models like GWPR in designing area-yield index insurance for farmers in Kenya and Tanzania. The study underscored the importance of integrating historical yield data with spatially referenced weather information to minimise basis risk.

In West Africa, Hellmuth *et al*. (2009) and Osgood *et al*. (2007) facilitated pilot weather index insurance programmes where GWR techniques were used to identify zones of homogenous risk. These zones served as the foundation for defining insurance units that reflect real-world climatic variation more accurately than administrative boundaries. In a study by El Ouardighi *et al*. (2020), GWPR was employed to analyse the spatial variability of agricultural yields across different regions in Morocco. This model enabled the identification of areas particularly sensitive to climatic variations by accounting for local effects and spatial dependencies. Through this approach, researchers were able to provide targeted recommendations for adapting agricultural practices and managing water resources, thereby contributing to the enhancement of the sector's resilience to climate-related challenges specific to each region.

The application of the GWPR model in the design of index-based insurance contracts entails the collection of climatic data for each agricultural season, stratified by regions or zones demonstrating homogeneity in yield response to climatic variables. The GWPR model is then employed to estimate expected agricultural production for each zone. When estimated yields fall below a predefined critical threshold, indemnities are determined based on the shortfall between the threshold and the observed yield, adjusted by the applicable compensation rate.

3. Method and data

Previous studies (Cai *et al*. 2012) have demonstrated that the relationship between climatic variables and crop yields exhibits significant spatial heterogeneity across different geographical regions. Despite this, many researchers continue to employ "global" regression parameters – those derived from the entire study area – which can be problematic. Such global estimates may fail to accurately capture the localised correlations between variables, thereby potentially compromising the precision of predictive models (Cai *et al*. 2012). To address this limitation, various methodologies have been developed to generate localised adaptations of traditional multivariate regression techniques with the aim to improve the spatial specificity and predictive accuracy of the models.

3.1 Method

This study utilises the geographically weighted panel regression (GWPR) model (Cai *et al*. 2012) to examine the hypothesis that weather variations have distinct effects on corn yields across different regions of Burkina Faso. It also explores how this spatial heterogeneity can be integrated into the design of local index insurance contracts. To facilitate comparison, we estimate the relationship between corn yields and climatic variables using various models that reflect different levels of spatial heterogeneity.

3.2 The global linear regression model

We use the global linear regression model as a reference. This model completely ignores the possibility of spatial heterogeneity in the relationship between corn yields and climatic variables; it is the pooled model. The model is written as:

$$y_{it} = \beta_0 + \sum_k \beta_k x_{itk} + \gamma t + \varepsilon_{it}, \tag{1}$$

where i represents a region and t indicates the year; y_{it} represents maize yields for region i in year t; x_{itk} indicates the k climatic variables for the region i in the year t; β_k is the coefficient of the climate variable k, constant across regions and time; γt is the trend; β_0 denotes the global constant; and ε_{it} is the error term.

If the relationship between corn yield and climate variables is well described by Equation (1), an identical index insurance contract is then proposed to producers in all regions. The spatial differentiation of index insurance contracts has no empirical basis.

Is the hypothesis of spatial homogeneity (Model 1 in Equation (1)) implicitly taken for granted by many authors as being reasonable in a context marked by increasingly large geographical areas? In order to answer this concern, we develop methods to take into account a possible spatial heterogeneity. If we consider all the coefficients of a regression, the spatial heterogeneity can be present in the form of different constants and/or different slopes. In this general case, we then speak of structural instability in space, or "spatial regimes" (Anselin 1988). Previous research does not support the hypothesis that β is indeed constant across regions. According to Cai *et al*. (2012), the hypothesis of the non-constancy of β across space is crucial if one is looking to develop an index insurance product that minimises geographical basic risk.

3.3 Fixed-effects models

The fixed-effects panel model is the most commonly used regression technique for analysing the relationship between climate change and crop yield (Deschenes & Greenstone 2007). The model is specified as follows:

$$y_{it} = \beta_{0i} + \sum_k \beta_k x_{itk} + \gamma t + \varepsilon_{it} \qquad (2)$$

The distinction between Model 1 and Model 2 (equations (1) and (2)) lies in the treatment of time-invariant regional effects. While Model 1 assumes a global constant, thereby excluding region-specific fixed effects, Model 2 incorporates such effects, accounting for structural heterogeneity across regions that remain stable over time. When the relationship between maize yields and climatic variables is adequately captured by Model 2, index-based insurance contracts can be differentiated solely by their threshold parameters, with a uniform indemnity structure across regions. The random effects specification was deliberately excluded, following the argument by Cai *et al*. (2012), as the regional fixed effects (β_{0i}) are likely to be correlated with the climatic regressors (X_{itk}), thereby violating the core assumptions of the random-effects model.

3.4 The random coefficient model

The random coefficient model suggests the presence of spatial heterogeneity in the form of different slopes. The standard model specifies a constant and random slopes for each region:

$$y_{it} = \beta_{i0} + \sum_k \beta_{ik} X_{ikt} + \gamma t + \varepsilon_{it}, \qquad (3)$$

with $\beta_{ik} = \beta_0 + \sum_l \beta_{ikl} z_{ikl} + \delta_{ik}$.

It is assumed in this formulation that Z is a vector of random variables capable of influencing the effect of the explanatory variables, X, on the dependent variable, Y.

The model uses a weighting inversely proportional to the regional variance, as regions with greater volatility of observations are involved with a lower weight in the estimation of the overall coefficient. We can then say that regional heterogeneity has been taken into account, although this model does not take into account the spatial dependence, i.e. the influence that a region exerts on other regions according to geographic, cultural or commercial proximity.

A relationship of type (3) (as in Equation (3)) suggests index insurance contracts that are totally different from one region to another at both the thresholds level and the progressivity level. Otherwise, the thresholds for triggering compensation differ from one region to another, but the proportional change in compensation from the level of the index between the trigger and the exit thresholds must also differ from one region to another.

3.5 The geographically weighted panel regression (GWPR)

Geographically weighted panel regression (GWPR) extends the capabilities of traditional panel data models by incorporating spatial non-stationarity, allowing regression coefficients to vary across geographic locations.

Geographically weighted regression (GWR) is a spatial analytical technique that employs weighted observations from neighbouring regions to estimate localised regression parameters at each spatial unit. The weights assigned to observations are inversely proportional to the distance between regions, reflecting the premise that geographically proximate areas exert a greater influence on each other's estimates.

The GWPR model is presented as a random coefficient model:

$$y_{it} = \beta_{i0} + \sum_k \beta_{ik} X_{ikt} + \gamma t + \varepsilon_{it} \quad (4)$$

Unlike the random coefficient model, in which the coefficients, βi, are treated as random variables, GWR assumes that these coefficients are deterministic functions of the spatial coordinates associated with each observation (Brunsdon *et al*. 1996; Fotheringham *et al*. 2002). The calibration of the GWR model is typically performed using a weighted least squares (WLS) approach, which presumes that data points in close proximity to a given location have a more significant impact on the estimation of the local parameters, βik, than those located farther away, thereby capturing spatial heterogeneity in the relationships under study.

The weighted least squares estimator is given by:

$$\hat{\beta}(i) = (X^T W(i) X)^{-1} X^T W(i) Y \quad (5)$$

where $\hat{\beta}$ is an estimate of β, and $W(i)$ is a diagonal spatial weighting $nt \times nt$ matrix, whose diagonal elements are the geographic weighting of the observations of each of the n neighbouring regions to the region i. The weighted least squares estimator is obtained by the following transformed model:

$$Py = \begin{bmatrix} \omega_{i1} y_1 \\ \omega_{i2} y_2 \\ \vdots \\ \omega_{in} y_n \end{bmatrix} \text{ on } PX = \begin{bmatrix} \omega_{i1} X_1 \\ \omega_{i2} X_2 \\ \vdots \\ \omega_{in} X_n \end{bmatrix}, \quad (6)$$

with ω_{ij} the geographical weighting of the observations of the region j relative to the reference region i (ω_{ii} = 1). Since we are in panel, each region contains T observations, and the extensive writing of the model gives

$$y^* = Py = \begin{bmatrix} \omega_{i1} y_{11} \\ \omega_{i1} y_{12} \\ \vdots \\ \omega_{i1} y_{1T} \\ \omega_{i2} y_{21} \\ \vdots \end{bmatrix} \text{ on } X^* = PX = \begin{bmatrix} \omega_{i1} X_{11} \\ \omega i_1 X_{12} \\ \vdots \\ \omega_{i1} X_{1T} \\ \omega_{i2} X_{21} \\ \vdots \end{bmatrix}. \quad (7)$$

y* is a *(nT, 1)* vector and X* is an *(nT, K)* matrix; the regression of y* on X* produces an estimate $\hat{\beta}$(i) of β(i), the coefficient vector for region i. Thus, the GWPR model is obtained by region-by-region estimation, while taking into account spatial dependencies between regions.

Similar to the model with random coefficients, the heterogeneity across regions pertains to all coefficients, including the slopes. Specifically, the relationship between yields and weather conditions varies from one region to another, underscoring the necessity to design a tailored index insurance contract for each region. According to Cai *et al*. (2014), the GWPR approach provides a more effective framework for integrating weather dynamics with crop productivity, particularly in study areas characterised by diverse topographical and climatic conditions.

In this study, we employ an adaptive bi-square kernel weighting function (Bruna & Yu 2013):

$$w_{ij} = \begin{cases} \left[1 - \left(d_{ij}/h_i\right)\right]^2 & if\ d_{ij} < h_i \\ 0 & otherwise \end{cases}, \tag{8}$$

where d_{ij} denotes the distance between region (i) and region (j), measured between their respective capital cities. The parameter h_i controls the radius of influence of the geographical data. Given the limited number of regions and the effects of migration, we assume that all regions influence each other, with the influence inversely proportional to the distance between them. To standardise the radius of influence across all regions, we set $(h_i = h_j = h)\ \forall\ (i,j)\ \in\ [1\ 2\ldots n]^2$). Furthermore, to ensure that all regions are incorporated into the estimation for each region, (i), we select (h) such that

$$h_i = max\left(d_{ij}\right)\ \forall\ (i,j) \in [1\ 2 \ldots n]^2. \tag{9}$$

This allows us to control the extent of the circle of influence of the geographical data. In our case, given the small number of regions and the effects of migration, we consider here that all regions have an influence on each other, but that this influence is inversely proportional to the distance between regions. To have the same radius of influence for all regions, we make the h_i identical for all regions $(h_i = h_j = h)\ \forall\ (i,j)\ \in\ [1\ 2\ldots n]^2$); and to ensure that all regions are integrated into the estimate for region i, we choose h such that:

$$h_i = max\left(d_{ij}\right)\ \forall\ (i,j) \in [1\ 2 \ldots n]^2. \tag{10}$$

In our case, the maximum distance (h) is 658 km, corresponding to the greatest separation between two regions, namely Dori and Gaoua.

In the context of geographically weighted panel regression (GWPR), the selection of kernel functions and bandwidth determination methods is a crucial methodological consideration, as both elements define the spatial weighting scheme and significantly influence the model's ability to capture spatial heterogeneity.

Kernel functions determine how spatial proximity influences the weighting of observations. Commonly used options include the fixed Gaussian kernel, which provides smooth, stable estimates for uniformly distributed data (Fotheringham *et al*. 2002), and the bi-square kernel, which emphasises nearby observations by assigning zero weight beyond a specified distance – useful for detecting sharp local variations (Brunsdon *et al*. 1996). Alternatively, adaptive kernels adjust bandwidths to include a fixed number of neighbours, making them ideal for unevenly distributed spatial data (Nakaya *et al*. 2005). In this study, an adaptive kernel was chosen to ensure that all regions are included in the bandwidth, based on the assumption that spatial influence decreases with distance, but never entirely vanishes.

Bandwidth selection further influences model performance. A large bandwidth risks over-smoothing, while a small one may yield unstable estimates. Cross-validation is commonly used to balance bias and variance (Fotheringham *et al*. 2002), while the Akaike information criterion corrected (AICc) is favoured for small samples due to its consideration of model complexity (Charlton & Fotheringham

2009). The Bayesian information criterion (BIC), which penalises model complexity more heavily, is suitable when overfitting is a concern (Wheeler & Tiefelsdorf 2005).

Given the limited number of spatial units in our study (eight locations), an adaptive bandwidth encompassing all observations was selected, as recommended in the context of small samples (Durrieu *et al*. 2014). Ultimately, the choice of kernel type and bandwidth must align with the spatial structure of the data and the analytical objectives. Our approach reflects the view that spatial interdependence is never zero, thereby supporting the use of adaptive methods for robust local estimation.

3.6 The variables

The dependent variable in this study is the average maize yield per hectare, expressed in tons per hectare. The climatic variables included in the analysis comprise 10-day cumulative rainfall (Rainfall), defined as the total precipitation (in millimetres) recorded over each 10-day period; the number of rainy days (NbRD) within the same interval; and the average temperature (Temperature) over the corresponding period. The selection of these climatic indicators is grounded in a robust body of empirical research, including studies by Christiaensen and Dercon (2007), Lobell *et al*. (2007) and Cole *et al*. (2009), which highlight their significant influence on agricultural productivity.

3.7 Data

The present study utilises daily meteorological data – including rainfall, temperature and number of rainy days – collected by the Burkina Faso National Meteorological Service from a network of 10 synoptic stations: Bobo Dioulasso, Bogandé, Boromo, Dedougou, Dori, Fada N'Gourma, Gaoua, Ouagadougou, Ouahigouya and Po. Given that the Fada N'Gourma and Bogandé stations are both located within the Eastern region, the Fada N'Gourma station was selected as representative, being the regional capital. Similarly, the Dedougou station was retained in lieu of Boromo to represent the corresponding agricultural region. Consequently, the analysis is based on data from eight synoptic stations corresponding to the eight agricultural regions of Burkina Faso. Maize yield data were obtained from the National Institute of Statistics and Demography (INSD) and cover the period from 1995 to 2009.

4. Results and discussion

This section presents the results of several models that examine the relationship between maize yields and various climatic variables, incorporating different degrees of spatial heterogeneity. In addition, the section explores the design of an optimal index-based insurance contract aimed at minimising basis risk through enhanced spatial integration.

4.1 Spatial variation in the relationship between maize yield and climatic conditions

This study investigates the relationship between maize yield and climatic variables through the application of four econometric models, each incorporating progressively greater levels of spatial heterogeneity.

Model 1, a global linear specification, operates under the assumption of complete spatial homogeneity in the relationship between yield and climatic factors. It demonstrates limited explanatory power, with climatic variables accounting for just over 50% of the variation in yield, and a residual sum of squares (RSS) of 12. Model 2, a fixed-effects panel model, introduces spatial heterogeneity in intercepts, while maintaining constant slopes for climatic variables across regions. However, it performs less effectively than Model 1, as reflected by an increased RSS exceeding 20. Model 3, a random-coefficients model, extends spatial heterogeneity further by allowing both intercepts and slopes to vary across space. The Hausman test results support the rejection of Models 1 and 2 in favour of Model 3, indicating significant structural variation in how maize yields respond to agroclimatic conditions regionally. These outcomes highlight the essential role of accounting for spatial heterogeneity in agricultural yield modelling. Model 4, the geographically weighted panel regression (GWPR) model, outperforms the preceding models in estimating maize yields from climatic variables (see Table 2). With an R^2 of 0.85 and a markedly lower RSS of 6.97, it offers the closest alignment between predicted and observed yields across diverse agroclimatic zones, affirming its suitability for spatially explicit agricultural analysis.

Table 2: Results of models 1, 2, 3 and 4

Dependent variable	Model (1)	Model (2)	Model (3)	Model (4) (GWPR)		
Corn yield				Min	Mean	Max
Rainfall	0.0031	0.0084**	0.0078	0.0040	0.0097	0.0150
NbRD	0.2382***	0.1805**	0.2042**	0.1343	0.2462	0.4249
Temperature	-0.1108***	0.0875	0.0229	-0.1201	-0.0279	-0.004
Trend (t)	0.0259**	0.0102	0.0121	-0.0103	0.0171	0.0296
Constant	2.9939*	-2.5540	-0.7737	-0.0738	0.0108	0.1152
Number of observations	112	112	112	112	112	112
R^2	0.5393	-	-	-	0.8577	-
Sum of square errors	12.0890537	20.1335919	15.2351394	-	6.9738	-

Notes: ***, ** and * represent a 1%, 5% and 10% degree of significance, respectively; NbRD = number of rainy days

This instability in the relationship between maize yield and climatic variables is evident in the spatial variability of the estimated coefficients (slopes) associated with the climatic factors, as presented in Table 3. The variation in these coefficients across geographic regions indicates that the sensitivity of maize yields to changes in climatic conditions – such as temperature, rainfall amount and number of rainy days – is not uniform. Instead, it reflects localised agro-ecological and socio-economic contexts, including differences in soil characteristics, farming practices and access to adaptation technologies. Such heterogeneity suggests that a one-size-fits-all modelling approach may overlook crucial region-specific dynamics, underscoring the necessity of spatially disaggregated analyses.

Table 3: Model 4 results by region

Regions	Rainfall	NbRD	Temperature	Trend	Constant	R^2
Centre	0.010706***	0.14652***	-0.01662***	0.02415***	0.11520***	0.6973
Centre-Sud	0.0040391	0.21969***	-0.12018*	0.02355***	0.04794***	0.8961
Est	0.010757***	0.19712***	-0.00775	0.00022	0.01508	0.9327
Hauts-Bassins	0.004567	0.42498***	-0.00411	0.01868**	-0.05177**	0.9423
Mouhoun	0.011856*	0.29308***	-0.01901**	0.02966***	-0.0738***	0.8578
Nord	0.015044***	0.20414***	-0.02492***	0.02468***	0.03311	0.7477
Sahel	0.013098***	0.134262**	-0.01388***	0.02588***	0.00646	0.8386
SudOuest	0.0079358	0.34990***	-0.01714*	-0.01031	-0.00559	0.9494

Notes: ***, ** and * represent a 1%, 5% and 10% degree of significance, respectively; NbRD = number of rainy days

The spatial analysis of climatic variables reveals differentiated impacts on maize yields across ecological zones. Rainfall significantly influences yields in drier areas, such as the Sahelian and sub-Sahelian zones, while in the well-watered Sudanian zone, its effect is not significant. In contrast, the number of rainy days, a proxy for the temporal distribution of rainfall, positively and significantly affects yields in all regions, although its impact is more pronounced in the Sudanian zone. Temperature exerts a uniformly negative influence on maize yield across all regions, likely because average temperatures exceed the optimal range for maize growth (Cai *et al*. 2014).

Although the findings indicate spatial instability in the relationship between maize yields and climatic variables, it is crucial to evaluate the temporal stability of this relationship. While the CUSUM tests did not detect structural instability in the model coefficients across the eight regions, the relatively short time span of the data does not provide sufficient assurance regarding the long-term reliability of these results. To obtain more robust conclusions, it is necessary to conduct stability tests using a longer time series.

4.2 Designing weather index insurance accounting for spatial heterogeneity

Traditional weather index insurance models frequently rely on uniform climatic thresholds (Model 1), grounded in the implicit assumption of spatial homogeneity in crop yield responses to climatic variables. However, this assumption oversimplifies the complex interactions between climate conditions and agricultural productivity. The empirical results demonstrate the limitations of such models: while the global linear model accounts for only 54% of maize yield variability, the geographically weighted panel regression (GWPR) model – by incorporating spatial heterogeneity and geographic dependence – raises the explanatory power to over 85%.

Alternative approaches, such as Model 2, attempt to address spatial variability by adjusting trigger thresholds or premium levels. However, these models fall short by neglecting localised climate-yield dynamics. This omission results in considerable inefficiencies, reflected in low explanatory power and a persistent misalignment between indemnity payments and actual yield losses.

Table 4: Results of Model 4 with rainfall alone as an explanatory variable

Region	Rainfall	Constant	R^2
Centre	0.01732***	0.10064***	0.6516
Centre-Sud	0.01742***	0.06698***	0.8674
Est	0.02202***	-0.01016	0.9157
Hauts-Bassins	0.03064***	-0.04289	0.9038
Mouhoun	0.00128***	0.02987**	0.8333
Nord	0.01883***	0.05646**	0.6935
Sahel	0.01864***	0.01264	0.8069
SudOuest	0.02606***	-0.00593	0.9392

The evaluation of rainfall as a single index variable in Model 4 (see Table 4) illustrates both the potential and the limitations of simplified index structures. Rainfall proves to be a strong predictor of maize yields in arid zones such as the Sahel, where it accounts for a substantial proportion of yield variation. However, its predictive relevance diminishes in semi-arid regions such as Centre and Nord, where adaptive farming practices and off-season cultivation attenuate the direct link between precipitation and yield. Cai *et al.* (2012) highlight the limitations of using variables such as temperature or the number of rainy days as sole indices linking yield to climatic variability. These observations underscore the importance of integrating multiple climatic indicators into index construction to enhance the precision and overall effectiveness of insurance products.

Beyond improved statistical fit, the GWPR model contributes to a significant reduction in average basis risk – estimated at 31.84%. This improvement is attributable to the enhanced accuracy of loss estimation achieved through spatially differentiated modelling, in contrast to the global linear specification.

Nevertheless, the study is not without methodological limitations. First, using administrative regions as the primary spatial unit of analysis may obscure considerable intra-regional variability. Employing more granular spatial data – at the provincial or departmental level – would facilitate more precise modelling of spatial effects. Second, treating the maize production cycle as a temporally homogeneous unit overlooks the distinct sensitivities of different phenological stages of climatic stress. Temporal disaggregation would therefore provide deeper insight into how climate factors affect crop yields across various stages of development. Third, the temporal scope of the dataset (1995 to 2009) constrains the ability to detect long-term structural shifts in the climate-yield relationship. While CUSUM tests reveal no structural parameter instability within the study period, a longer observation window would support more robust parameter stability testing. Finally, the exclusion of five administrative regions due to data limitations, despite the fact that the Sahel Crop Insurance does not currently cover these regions, reduces the national representativeness of the model and poses a significant obstacle to the broader objective of achieving universal agricultural insurance coverage. In addition, this can represent a methodological limitation, as uncovered regions may influence those that are covered, thereby presenting a constraint of the current approach.

5. Conclusion

This study investigated optimal methods for integrating spatial heterogeneity into the design of index-based agricultural insurance. Using maize yield and climate data from eight regions in Burkina Faso, four econometric models were evaluated to capture spatial variations in yield responses to climatic factors, particularly rainfall. The results indicate that conventional models such as OLS, fixed effects and random coefficient approaches inadequately represent spatial complexity in the presence of autocorrelation and inter-regional variability. In contrast, the geographically weighted panel regression (GWPR) model offers significantly improved explanatory power and predictive accuracy by accounting for spatial dependence and parameter heterogeneity.

The analysis reveals pronounced regional disparities in climate-yield relationships, reinforcing the need for locally calibrated insurance contracts. Effective index insurance design must incorporate spatially differentiated parameters – including trigger thresholds, exit points and payout mechanisms – to reduce geographic basis risk. Failure to do so may contribute to low uptake and high attrition rates in existing weather index insurance programmes, driven by a persistent mismatch between indemnity payments and actual yield losses.

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