The Geography of Climate Insecurity: Current State and Future Prospects for Northern Nigeria

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Abstract

This paper presents a geographical characterization of the current and future climate insecurity landscape at local level in Northern Nigeria, with an emphasis on the spatially varying effect of cereal prices on moderating the climate-conflict association. Complex local contexts in the study region challenge the spatial stationarity assumption made in previous studies. We take one step further and estimate geographically weighted regressions that account for spatial regime shifts to improve model performance and offer richer insights. Based on monthly data from 257 Local Government Areas (LGA) over 2016-2019, results corroborate that on average, the positive empirical association between temperature anomalies and violent conflicts is strengthened when prices of rice and maize increase in the wake of temperature anomalies. The magnitude of this amplifying effect at local level, however, can be three times greater than the average effect at national level assuming spatial homogeneity. The LGA-specific estimates identify and contextualize the climate insecurity hotspots, which are then integrated with climatic projections to extrapolate the possible trajectories of climate-related conflicts to the near term (2030–2040). The empirical analysis highlights the need to develop localized, forward-looking evidence for prioritizing preventative action and fostering climate-resilient peace in Northern Nigeria and similar vulnerable regions.

Keywords: spatial heterogeneity, conflict, temperature anomalies, agricultural commodity prices, Nigeria

1. Introduction

In Africa, agriculture-relevant climate hazards may interact with existing vulnerabilities in agrifood systems and indirectly exacerbate insecurities. This is because the majority of the African population depends on rainfed agriculture (Freeman, 2017) and their access to stable food markets are limited (Kakpo, Mills, & Brunelin, 2022). Abnormal rises in temperature during crop growing seasons have been responsible for yield losses (Barrios, Ouattara, & Strobl, 2008), the adverse influences on incomes and food affordability may reduce the opportunity cost of joining conflicts (Maystadt & Ecker, 2014) and trigger social unrest, grievances (Bush, 2010), and violence (Berazneva & Lee, 2013).

Within a country, the hazard of climate shocks and its disruption on the agri-food system are often not evenly distributed (Schlenker & Lobell, 2010). Due to each region's distinct and unique combination of socio-economic and agricultural-related characteristics, vulnerability in food system does not necessarily coincide with where the shocks are more severe (Ide, 2017). In fact, the presence of vulnerability may condition on a large group of location-specific features, both observable (such as market prices, infrastructure, agricultural production, natural resources, and historic conflicts) and unobservable (such as the level of market integration, community and inter-tribal dynamics, informal resource sharing and support system, political institution, local conflict resolution mechanism, and social cohesion). While in some Western African countries may be relatively homogeneous internally, other countries like Nigeria often have considerable internal diversity stemming from social-economic and agroecological complexity. Characterizing the geographical dispersion of climate security is therefore critical to improve our understanding of local vulnerability to climate impacts in Nigeria and similar countries.

The spatial dispersion characterizing the climate insecurity landscape can bring two challenges. (1) Practically, spatial dispersion implies that peacebuilding efforts and humanitarian intervention will require localized analysis and tailored support. As emphasized in the 6th IPCC Report on Climate Change 2022, there is the "*urgency of holistically addressing climate-related vulnerabilities as well as conflict, to sustain peace and development in line with context specificity*." (2) Empirical, it is difficult to model explicitly all the observable and unobservable location-specific features that influence vulnerability while also accounting for similarity among neighboring areas in a flexible yet tractable framework. Additional complexity comes from the temporal dimension. Climate insecurity may be aggravated by other root causes of violence and persistent poverty in currently conflict-affected communities to threaten peace and development, but they may also manifest in the future in different areas that are currently less conflict affected but are more susceptible to climate variabilities.

Extensive research has been conducted on the relationship between climate and conflict and how it manifests itself through the influence of the agricultural market. The majority of findings demonstrate that extreme weather events may not directly cause conflicts, but they may be indirectly linked to violent incidents through a variety of channels (Miguel, Satyanath, & Sergenti, 2004); Maystadt & Ecker, 2014). Quantitative results from this stream of research generate *average impact* of climate induced price change on conflict, given historic observations of climate hazards (for example, (Maystadt & Ecker, 2014). Others, such as Harari & Ferrara (2018) establish the climate-conflict relation at a disaggregated level (cell). Their analysis shows that weather shocks during the crop growing season negatively affect civil conflict, assuming key estimated parameters are constant across locations. Where local contexts vary only to a limited extent, assuming constant marginal effect of climate-related price change on conflict may be informative. In other cases, focusing on the average effect of price change may veil local conditions. Vesco et al (2021) focus on the important role of spatial heterogeneity in the distribution of agricultural production and discovered that climate extremes and crop production concentration increase the predicted likelihood of conflict. Yet their empirical model assumes that the marginal impact of agricultural production exerts a constant effect, and the country-level analysis prevents the illustration of a more granular picture that could help inform targeted intervention at local level.

This study offers a spatial depiction of the current state and future prospects of climate-conflict association in Nigeria, focusing on how agricultural price changes following weather shocks may strengthen this association. We characterize this pattern in northern Nigeria over the period 2016–2019. Climate shocks are captured by anomalies in maximum temperature. The estimations take the smallest administration in Nigeria as the unit of observation, and then regress the incidence of violent conflict on temperature anomalies, staple food prices (rice, maize, sorghum and millet), and the interactions of these two variables. This is done by locally weighted regressions, which use each location's own information, and the weighted information from neighboring locations to account for spatial heterogeneity and autocorrelations.

This paper complements the empirical climate-conflict literature in three directions. First, we explore within-country heterogeneity embedded in climate-conflict relations through a spatially explicit framework. Compared to previous contributions, we estimate the locally varying relationship between climate, conflict, and agricultural commodity prices, which robustly improves the predictive performance of the model compared to models that impose homogeneity. Second, as an extension to the existing literature that relies on historic observations of climate data, we incorporate climate predictions to extrapolate future trajectories of climate insecurity. In some areas, the dry conditions are projected to be more severe than the national average. Accounting for this additional source of heterogeneity constitutes an important contribution that brings our understanding of the climate security landscape one step closer to possible future conditions. An additional novelty relates to the careful validation and interpretation of the predictive uncertainty beside point estimates to overcome the inferential caveat of the methods.

The estimations from geographically weighted regression (Brunsdon, 1996) produce two novel sets of results. First, the results imply that districts are heterogeneous, and that both observed and unobserved factors can condition the effect of the agricultural market in shaping the climate security association. There is systematic dispersion across locations in terms of how the association between temperature anomalies and conflict is amplified when staple crop prices increase following temperature anomalies, and the variability is unlikely driven by overparameterization. We also observe that Zamfara State and the northern part of Niger State have the highest risk of evolving into future hotspots of climate-related conflicts. Second, the climate security landscape is then contextualized with socio-demographic layers and integrated with climate projection to show diverse future trends in climate-driven price shocks. For example, temperature anomalies exert a harmful effect, especially in north-eastern regions such as Borno and Sokoto states, where areas have been plagued by bandit conflicts between the state government and different gangs and ethnic militias, as well as herder-farmer/herder-herder conflicts (Chukwuma, 2020). Although the empirical analysis is conducted using data from northern Nigeria, our methodological framework can be extended to other regions to help provide locally pertinent policy evidence for the development of climate-resilient peace in similar contexts, or to study the moderating effect of other possible intermediate factors through which climate variability may be associated with conflict.Second, the climate security landscape is then contextualized with socio-demographic layers and integrated with climate projection to show diverse future trends in climate-driven price shocks. For example, temperature anomalies exert a harmful effect, especially in north-eastern regions such as Borno and Sokoto states, where areas have been plagued by bandit conflicts between the state government and different gangs and ethnic militias, as well as herder-farmer/herder-herder conflicts (Chukwuma, 2020). Although the empirical analysis is conducted using data from northern Nigeria, our methodological framework can be extended to other regions to help provide locally pertinent policy evidence for building climate-resilient peace in similar contexts, or to study the moderating effect of other possible intermediate factors through which climate variability may be associated with conflict.

The remainder of this study is structured as follows: In Section 2, we summarize the background that motivates the focus on spatial heterogeneity, followed by a review of the conflict-climate association and the role of agricultural commodity prices in the context of Nigeria. Section 3 describes the empirical motivation and strategy to extract local estimates using geographically weighted regression (3.1), the selection of observed and anticipatory hotspots (3.2), the rationale and process to incorporate future climatic variability (3.3), and robustness check strategies (3.4). Section 4 begins with a description of the study area selection (4.1) and introduces the variables and data sources (4.2). Section 5 presents the main results at aggregate level and the granular variability (5.1), the selection of current and anticipatory climate insecurity hotspots and their social-demographic characteristics (5.2), the trajectory of future climate-conflict linkage given predicted climatic conditions (5.3), and robustness check using different accumulation period of temperature anomaly, different spatial kernels, and with permutation based econometric diagnostic (5.4). Section 6 concludes.

2. Background

Northern Nigeria has been plagued by violence and instability that seriously hamper the development and livelihood. The conflict has been fueled by a number of factors including political and economic marginalization, religious extremism, and ethnic tensions. Banditry and terrorism have persistently plagued the Northern regions (Nextier, 2022). In 2009, Jama'atu Ahlis Sunna Lidda'awati Wal-Jihad (People Committed to the Propagation of the Prophets Teaching and Jihad) also known as Boko Haram, radicalized and became violent, while in 2012, Jama'atu Asaril Muslimina Biladis Sudan (Vanguards for the Protection of Muslims in Black Africa), often referred to as Ansaru, emerged as a split of Boko Haram. As a result, in

2013, the Nigerian government launched large-scale military campaigns against Boko Haram and Ansaru, backed by a Joint Task Force of police, military, and civilians providing intelligence, and declared states of emergency in Adamawa, Borno and Yobe states.

The situation has been further complicated by the scarcity of natural resources and pressure from climate change. North-western states near the Lake Chad have reported increases in the frequency and duration fo droughts over the last 40 years which has been attributed primarily to rising temperatures (World Bank, 2021). In the northern part of the country, the average maximal temperature has increased over the past fifty years. Since the last significant drought in 1983, the average temperature increases from 2.9°C to 5.7°C (Federal Ministry of Environment, 2021). The rising temperature has caused an adverse impact on the agricultural sector which constitutes more than 20% of the national GDP and 39% of the workforce (USAID, 2022). For example, drought is one of the major constraints to crop production, especially rice and maize (Kamai & Omoigui, 2020).

Climate-induced production failures have led to income shocks and commodity price fluctuations (Olurounbi, 2021). Alongside political or religious mobilization and competition over resource**s,** this may be associated with instability and insecurity (Fudjumdjum, Leal Filho, & Ayal, 2019)**.** For example, in Borno State, the armed conflict involving Boko Haram has gained momentum since 2009. Responses by state security forces and vigilante groups have led to forced mobility, food insecurity, and violence (Day & Caus, 2020). In this setting, climate-related livelihood losses have not only escalated organized crime (Nett & Rüttinger, 2017) but also made local populations more susceptible to recruitment (Ewi & Salifu, 2017). Still in Northern Nigeria, drought and shrinking river bodies are some of the leading causes of clashes between pastoralists and farmers (Olurounbi, 2021).

Studies on the price-conflict interaction capture two channels linking agricultural market vulnerability to conflict. Consistent with the opportunity cost theory, for producers, higher commodity prices increase their opportunity cost of joining conflict and could reduce conflict, while the opposite is true for consumers (Abidoye & Calì, 2021). Previous literature has also indicated that the agricultural commodity markets in African including Nigeria can be characterized by limited absorbing capacity of shocks, low farmer revenues, low-income consumers, and high consumer food prices (Bergquist & Dinerstein, 2020). Acute food and nutrition insecurity could lead to widespread desperation and tip the scale towards acts of violence by stoking existing tensions (Von Uexkull, 2014). For instance, in remote and agricultural areas in Northern Nigeria, the most affected households by climate-induced market shocks are primarily subsistence farmers who face a low opportunity cost for engaging in anti-social behavior. They also tend to spend a disproportionate share of their income on basic foods. As such, volatility in staple food availability and high prices in relation to income can be especially triggering for social upheavals (Bellemare, 2015).

Literature also indicates that in Nigeria, the impact of climate change on major crop production and market prices may vary considerably between regions due to its diverse agroecological landscape and political fragmentation, and the same climate stressors can cause different levels of price (Bosello, Campagnolo, & Cervigni, 2018).

3. Empirical strategy

3.1 Geographically weighted regressions

This study aims to examine the empirical relationship between climatic shocks, agricultural prices, and violent conflicts in Northern Nigeria, to determine if such a relationship exhibits spatial heterogeneity across districts. Besides the rationale and background outlined in Section 2, our emphasis on spatial heterogeneity is also motivated by a few important empirical factors. First, conflicts in Northern Nigeria are highly concentrated in a few areas. Between 2016 and 2019, we observe 1,925 violent conflicts in total and 60% occurred in 12 LGAs. Rabah, an LGA in Sokoto State, for instance, experienced five times more conflict than an average LGA. Second, the occurrence of climate variability has historically been more prevalent in the northeast part. For these reasons, assuming the empirical relationship between climatic shocks, agricultural prices, and violent conflicts in each location is the same as northern Nigeria average may generate upward or downward bias for local implications.

Possible variations in relationships over space, such as those described above, are referred to as spatial nonstationarity. Econometrically, it requires the estimation of locally varying processes that allows regime shift, which motivates us to use geographically weighted regression, a useful method for exploring possible spatial heterogeneity. Geographically weighted regression employs spatial weights to determine the relationship between climatic stressors, agricultural commodity prices, and violent conflicts. These geographical weights are relatively greater for observations located close to the regression point than for those located further away. This method allows examining the spatial variation of estimates and comparing the results to those estimated through a global model. It also implicitly takes into account the spatial autocorrelation in neighboring areas because agricultural markets can be geographically integrated and price shocks in one region can affect neighboring regions.

We examine the location-dependent association between crop prices changes in the wake of temperature anomaly and conflict. Four separate models are estimated for rice, maize, sorghum, and millet, respectively. For each crop equation, the price of major substitutes crop is controlled. Since rice and maize are the major staple food in Nigeria, for the rice equation, maize price is controlled and for the maize equation, rice price is controlled. For sorghum and millet, both rice and maize prices are controlled on the right-hand side.

Rice: $Conflict_{im} = \beta_0^{rice}(i) + \beta_1^{rice}(i)temp\ anomaly_{im}\ +$
$\beta_2^{rice}(i)rice\ price_{im}\beta_3^{rice}(i)temp\ anomaly_{im} \times rice\ price_{im} +$
$\beta_4^{rice}(i)maize\ price_{im} + \varepsilon_{im}$ (1)

Maize: $Conflict_{im} = \beta_0^{maize}(i) + \beta_1^{maize}(i)temp\ anomaly_{im}\ + \beta_2^{maize}(i)maize\ price_{im} +$
$\beta_3^{maize}(i)temp\ anomaly_{im} \times maize\ price_{im} + \beta_4^{maize}(i)rice\ price_{im} + \varepsilon_{im}$ (2)

Sorghum: $Conflict_{im} = \beta_0^{sorghum}(i) + \beta_1^{sorghum}(i)temp\ anomaly_{im}\ + \beta_2^{sorghum}(i)sorghum\ price_{im} +$
$\beta_3^{sorghum}(\boldsymbol{i})temp\ anomaly_{im} \times sorghum\ price_{im} + \beta_4^{sorghum}(i)rice\ price_{im} +$
$\beta_5^{sorghum}(i)maize\ price_{im} + \varepsilon_{im}$ (3)

Millet: $Conflict_{im} = \beta_0^{millet}(i) + \beta_1^{millet}(i)temp\ anomaly_{im}\ + \beta_2^{millet}(i)millet\ price_{im} +$
$\beta_3^{millet}(\boldsymbol{i})temp\ anomaly_{im} \times millet\ price_{im} + \beta_4^{millet}(i)rice\ price_{im} +$
$\beta_5^{millet}(i)maize\ price_{im} + \varepsilon_{im}$ (4)

In all four equations, $Conflict_{im}$ stands for the number of conflicts in district i in month m. $\beta_{.}(i)$ are the location-specific parameters to be estimated. The key parameter of interest is the parameter for interaction term of crop prices and temperature anomaly. Larger estimated coefficient suggests greater increase in conflict frequency in the face of climate-induced price change. Since conflict is a count variable and cannot take negative values, the function is estimated through Poisson regression. Fixed effects at the state level are included, capturing important unobservable characteristics such as local endowment, community informal resource sharing and support system, political institutions, traditional conflict resolution mechanism, social cohesion and that may influence violent conflicts but do not change or change only slowly over time. Estimated coefficients from the equation (1) to (4) are extracted for each LGA. The key parameter of interest is the parameter for interaction term of crop prices and temperature anomaly. Larger estimated coefficient suggests greater increase in conflict frequency in the face of climate-induced price change.

Equations (1) to (4) are estimated for each LGA using observations from neighboring LGAs through a kernel function. Two important parameters are involved in the estimation: The size of "neighborhood" is determined by kernel bandwidth, and the importance of each neighbor is determined by a weighting function. The size of bandwidth, which is the distance (calculated as the distance between LGA centroids) beyond which a value of zero is assigned to weigh LGA, can directly alter parameter estimates and affect model performance. Larger bandwidths include a larger number of LGAs receiving a non-zero weight and more LGAs are used to fit a local regression. This is more appropriate where the data is sparse. To determine the optimal bandwidth, a cross-validation approach is applied which involves defining neighbor windows to minimize both bias and variances. In the main specification, adaptive bandwidth is calculated such that the size of neighborhood is adjusted according to data point sparsity. Denoting bandwidth as h, the weight is a function of distance d between any two locations, specified in equation (5):

$$w(d_{ij}) = 1 - (d_{ij}/h)^2 \; if \; d_{ij} < h \tag{5}$$

With local regression, estimated coefficients from the equation (1) to (4) are then extracted for each LGA. Since the estimation is not model-dependent, this framework is also able to correctly characterize the homogeneity and stationarity, if the relationship between temperature anomaly, agricultural commodity price, and conflict displays such characteristics.

3.2 Observed and anticipatory hotpots selection

The framework also allows us to identify observed and anticipatory climate insecurity hotspots. Observed climate insecurity hotspots are areas that are affected by conflicts and are highly sensitive to price shocks induced by temperature anomaly episodes. Anticipatory hotspots are areas which are relatively less affected by conflict but may become climate insecurity hotspots in the future given their high conflict-sensitivity to the changing prices in the aftermath of temperature anomalies. For both types of hotspots, we only select those of which the coefficient of the temperature-price interaction is significant at 10% level.

For observed climate insecurity hotspots, we further classify “medium” hotspots as districts that rank above the median of the distribution of the interaction slope (i.e., the estimated association between temperature anomaly-induced price changes and conflicts), and above the median of the distribution of the actual monthly conflict, and “severe” hotspots as LGA that are above the 75 quantiles for he estimated coefficient of interaction term and below 25 percentiles of average monthly conflicts. The selection of medium (severe) anticipatory hotspots follows the same criteria, except that these LGA rank below the median (25% quantile) of the distribution of the actual conflicts. Together, these two types of hotspots illustrate the observed climate-conflict association conditional on shock-related crop prices changes, and the future prospects of this association, should the market vulnerability evolve under worsening climate conditions.

3.3 Future climate-conflict extrapolation

Another source of heterogeneity comes from the location of future climate shocks, which can shed important insights on the trajectory of climate-related conflicts in the near term. Collier et al (2008) suggest that the combination of an already difficult climate, significant projected climate change, and the limited adaptation capacity make Africa much more sensitive to expected future climate change than other regions.

Within Northern Nigeria, the occurrence of dry conditions may also impact the study region differently. Although the precise pattern of future high temperature for each area is not predictable, the northeast is projected to experience the largest projected increase from present day climate by 2050. Taking this future climatic condition into account when projecting potential influence on climate-related conflict can inform how the climate insecurity landscape may evolve.

Following previous practices, we focus on the near term (2030-2040) to refrain from extrapolating the results too far into the future where there may be possibilities for food system transformation and adaptation (Harari & Ferrara, 2018). Further in the future, the uncertainty with respect to the overall structure of the agriculture sector and the way food systems will have transformed may impact the results presented here. According to the World Climate Research Programme's Sixth Coupled Model Intercomparison Project, known as CMIP6 (O'Neill et al., 2016), in Representative Concentration Pathway (RCP) 4.5 emission scenario, the total number of days in Nigeria with high temperatures (defined as days in a year during which the temperature is above 35 degrees Celsius) will increase by 17 days with median probability by 2030, and this number will increase by 29 days by 2040. The number of days with temperature higher than 35-degree Celsius may be a good proxy for future climate conditions where temperature may likely to be abnormally high. In fact, most of high temperature conditions are anticipated not only in Borno state, which already experiences frequent temperature anomalies during the study period of 2016-2019, but also in north-western Nigeria, including Sokoto, Kebbi, and Zamfara States. These regions had relatively fewer high temperatures episodes in the past, but are projected to face high stress in future climate conditions, especially for the next 20 years. We first derive the total number of days with temperature higher than 35-degree Celsius for each district in 2030 and 2040, this number is compared with that in 2019 to calculate the percentage increase in high temperature days. This district-specific projection information is multiplied by the estimated marginal parameters of the interaction term from the main specification to get the estimated increase in conflict conditional on price increase, assuming that the percentage change in price will likely follow similar trajectory in the future as in the historic period. We repeat the exercise in the right panel in Figure 2 on three selected LGAs that have representative trajectories of estimated percentage increase in violent conflict.

3.4 Robustness checks and placebo tests

Robustness checks

To test whether our analysis is sensitive to longer periods of temperature anomaly, we repeat the main model, but this time use a six-month accumulation period of temperature anomalies. Since the spatial kernel can influence the model's performance directly, as a further robustness check, we also apply different bandwidth selections through cross-validation with fixed bandwidth and different kernel functions. We also apply different weighting functions besides Gaussian kernels.

Placebo test

Due to the locally weighted regression, observations are used repeatedly, and it is more likely that random noise is mis-interpreted as actual trend. Moreover, to test if the results are generated from spurious regression, we conduct permutation based econometric diagnostic tests (similar to placebo tests) using randomly generated spatial pattern. The permutation is based on random spatial coordinates. If the spatial heterogeneity is just an artifact of non-linearity or random noise in price, one would see the main results located on the center of the random permutation distribution.

4. Data

4.1 Geographical scope of this analysis

The geographical scope of this analysis is northern Nigeria. We focus on this region for several contextual considerations. As described in the Background section, this region is particularly vulnerable to shocks and stressors. Second, the majority of agricultural commodity data is available for northern Nigeria. Out of the 40 agricultural commodity markets monitored by World Food Programme, 37 are located in 29 Local Government Areas (LGA) in the north, particularly in Abuja, along the Benue River and Niger River, and from the Jos Plateau to the northern border between Nigeria and Niger. Second, most of the violent conflicts also occur in the northern LGAs. For example, Maiduguri has witnessed a disproportionately large number of conflicts between 2016 and 2019. From a policy perspective, climate-related security risks may be of greater urgency in the north. Therefore, this study focuses on 257 northern LGAs from 13 states. The red shaded areas in Figure 1 depict the study region. Red dots represent the location of agricultural commodity markets.

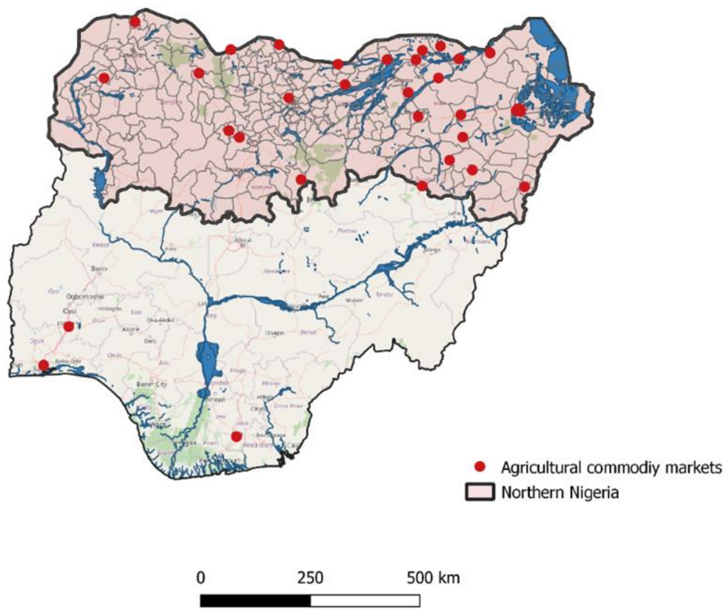

Figure 1. Study region

4.2 Variables

Violent conflicts

The dependent variable is the number of violent civil conflicts at the LGA level that occurred each month between 2016 and 2019. The conflict data is obtained from the Armed Conflict Location & Event Data Project (ACLED) (Raleigh, Linke, Hegre, & Karlsen, 2010) which has been widely adopted in previous climate-conflict studies (for example, Maystadt & Ecker, 2014). ACLED is a disaggregated dataset that collects the dates, actors, locations, and types of reported violence (Raleigh, Linke, Hegre, & Karlsen, 2010). It has six event types and 25 sub-event types of conflict. This enables us to concentrate on the types of conflict that are most relevant to climate-induced conflict measurement. Conflict in this study is defined as violence against civilians, explosions and remote violence, and battles. On average, between 2016 and 2019, each LGA experienced an average of 1.7 conflicts per month. Figure A1 in the Appendix displays the average number of monthly conflicts in the region of study. More conflicts occur in the north-eastern and north-western areas, especially northern Rabah in Sokoto, Gwoza and Maiduguri in the State of Borno, and Rafi in the state of Niger. Boko Haram has been one of the major actors involved in conflicts primarily fought between illegal arms/ethnic militias and state governments. In contrast, the middle region of Kano State and the western part of Bauchi are less conflict-affected.

Climate variability

The climate variability is captured by the maximum temperature anomalies for the three and six months preceding the date on which agricultural commodity prices were recorded. A maximum temperature anomaly refers to a deviation from the long-term average temperature. A positive anomaly indicates that the observed temperature is warmer than the long-term average, whereas a negative anomaly indicates the opposite. Warmer temperatures can increase evaporation, thereby reducing surface water and drying out soil and vegetation. In the main specification, the variable *temperature anomaly* is an indicator variable that takes value 1 for three-month anomaly temperature being positive. In robustness check, this variable takes value 1 for six-month anomaly temperature being positive. Between 2016 and 2019, major temperature anomaly episodes occurred in the Borno and Kaduna States, especially in Igabi, Kauru, and Chikun District.

Agricultural prices

We focus on four crop commodities that are locally produced in Nigeria: rice, maize, sorghum, and millet. These crops are Nigeria's major staple food. The original monthly crop price data is assembled from the World Food Programme (WFP) Price Database, which consists of 37 markets where WFP monitors and collects price information. Given that these are the primary agricultural commodity trading markets, it is reasonable to assume that both buyers and sellers may cross state and LGAs borders to reach these spatially connected markets (Hastings, Phillips, & Ubilava, 2022). To account for this, prices are interpolated using inverse distance weighting, a spatial statistical method that uses known values (i.e., where we have market data) to estimate the value at an unknown point (the areas without market data). Formally, the spatially interpolated prices $price(x)$ have the following form:

$$price(x) = \begin{cases} \dfrac{\sum_{i=1}^{N} \dfrac{1}{d(x,x_i)^2} * price(x_i)}{\sum_{i=1}^{N} \dfrac{1}{d(x,x_i)^2}} & if\ 0 < d(x,x_i) < 50\ km\ for\ i = 1, 2 \dots N \\ price_i & if\ d(x,x_i) = 0 \end{cases}$$

Where x denotes an interpolated point where market price information is not available, x_i is an interpolating point where market price information is available, d is the distance from the known market point x_i to the unknown point x, N is the total number of known markets points used in interpolation and in our case equals 37. The interpolated price raster is then averaged by LGA for each month. We refrain from interpolating too far into areas without price information and we only interpolate each point within 50 km distance from each market point to reflect a reasonable geographical scope of trade. Figure A2 in the Appendix shows the average interpolated prices of rice (top left) maize (top right) sorghum (bottom left) and millet (bottom right) between 2016 and 2019. Table A1 in the Appendix presents the summary statistics of all key variables including prices, violent conflicts, and temperature anomalies.

5. Results

5.1 Main estimation results

Table 1 summarizes the main findings from both the global and local Poisson regressions. We begin with the "global" parameters which represent the average relationship in northern Nigeria between abnormal temperatures, prices volatility and conflicts estimated through Poisson regression using all the observations (non-weighted). The key variable of interest is the interaction term *Three-month Temperature anomaly=1×Price,* of which the coefficients are significant for rice and maize. The positive sign suggests that the association between temperature anomaly and conflict is amplified when rice and maize prices rise following a temperature anomaly episode. On average, the price of rice increases from 0.63 USD/kg to 0.71 USD/kg following a temperature anomaly, maize increases from 0.24 USD/kg to 0.28 USD/kg, sorghum from 0.25 USD/kg to 0.31 USD/kg, and millet from 0.27 USD/kg to 0.31 USD/kg. These mean differences are all significant at 1%. With these observed price changes, holding everything else constant, at the observed price change before and after a temperature anomaly for each crop, the number of conflicts increased approximately by 11.5% with respect to rice price change, 21.5% with respect to maize price change, 29% with respect to sorghum price change, and 22.5% with respect to millet price change.

The global Poisson regression offers a useful depiction of the overall landscape across the study region. The results from geographically weighted Poisson regressions picture the local dispersion and show the improvement in model performance compared to the non-weighted global model. Econometrically, local regressions improve the goodness of fit across models and the information criteria also favor local models for all four crops, with greater R square. The consistently smaller AIC implies that the local models outperform in all four models. Second, since the parameters vary by location, the minimum, median, mean and maximum of these local parameters are reported to characterize the distribution. For all four crops, the coefficients of interest show considerable disperse pattern.

Figure 2 plots the coefficient of the interaction term extracted from the geographical regression (left), its standard error (middle) and the percentage increase in conflict associated with price increase following temperature anomaly, evaluated at the observed level of price change (right). By virtually examining the coefficient of the interaction term coefficient, for all the four staple crops, there is a complex surface of marginal effect. For instance, the coefficient of the rice price-temperature anomaly interaction term ranges from 0.2 to 4.08. The geographical non-stationarity in the price-temperature nexus is also corroborated by the fact that the standard deviation of the spatially varying parameter estimates for the interaction term (1.27 for rice, as an example) can be up to three times greater than the standard deviation of global parameter estimate (0.42 for rice, reported in Table 1).

Table *1*. Estimation results from main model

	Rice			Maize			Sorghum			Millet		
ESTIMATOR	**Poisson (Global)**	**Poisson (GWR)**		**Poisson (Global)**	**Poisson (GWR)**		**Poisson (Global)**	**Poisson (GWR)**		**Poisson (Global)**	**Poisson (GWR)**	
Three-month Temperature anomaly=1 × Price	1.44** (0.42)	*Min*	0.20	2.38*** (0.71)	*Min*	1.14	1.18 (0.62)	*Min*	1.01	1.19 (0.77)	*Min*	1.02
		Median	3.05		*Median*	2.24		*Median*	2.17		*Median*	2.62
		Mean	2.41		*Mean*	2.33		*Mean*	2.31		*Mean*	2.60
		Max	4.08		*Max*	3.62		*Max*	3.69		*Max*	4.15
State FE	YES	YES		YES	YES		YES	YES		YES	YES	
Year FE	YES	YES		YES	YES		YES	YES		YES	YES	
Month FE	YES	YES		YES	YES		YES	YES		YES	YES	
Control: maize price	YES	YES		/			YES	YES		YES	YES	
Control: rice price	/	/		YES	YES		YES	YES		YES	YES	
Bandwidth	/	Adaptive		/	Adaptive		/	Adaptive		/	Adaptive	
R-square	0.16	0.22		0.17	0.23		0.15	0.27		0.16	0.22	
AIC	1277	1230		1267	1216		1165	1121		1208	1160	
Number of Obs.	951	951		951	951		845	845		896	896	

*Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors for global models are in parathesis. Global estimator refers to the Poisson fixed effect model that uses all the data points. The dependent variable is the number of monthly violent conflicts. Excluding months for which only one agricultural market information is available. Temperature anomaly is a dummy variable equals one if three-month temperature anomaly is above 0. The estimation uses 257 northern LGAs from 13 States. The unit of analysis is LGA-month for both global Poisson fixed effect regression and the GWR Poisson regression estimates. All models include state level fixed effects and month fixed effects. Bandwidth based on cross-validation.*

Both positive and negative spatial autocorrelation in the estimated interaction term parameters can be found for the mediating effect of maize price. The positive autocorrelation is consistent with our expectation, as adjacent areas may share more similarities in these abovementioned features, thus demonstrating similar responses to the adverse impacts. On the other hand, among several adjacent LGAs in Kano and Kaduna states, the impact of maize price changes following temperature anomaly episodes can differ significantly. This could be due to the spatial distribution of maize production in Northern Nigeria, since Kaduna State is Nigeria's largest producer of maize and its market infrastructure is more formalized, potentially allowing for easier adjustment to production shocks and a smaller impact from income shocks. Moreover, the trend surface of this complexity cannot be represented by a simple linear or quadratic global trend, implying the precision gain from estimating local relationships.

Besides the points estimates, the statistical inferences of the local parameters are visualized in the middle panel of Figure 2 which shows clearly that the standard errors are not uniformly distributed and are larger for areas in the southern part of the Borno state for rice, maize, and millet and larger in the western states, including Zamfara and Sokoto for sorghum, and the point estimates for those areas are less precise. For areas with small standard error, such as the eastern districts with respect to the marginal effect of sorghum price, we have higher confidence that the observed spatial heterogeneity is more likely driven by actual differences in spatial pattern rather than random local idiosyncrasies.

The right panel of Figure 2 depicts the percentage increase in conflict conditional on the observed level of price change following temperature anomalies. Given the observed degree of price increases, the conflict increase is greatest in Borno State for rice and millet and larger in Sokoto State for maize. Visual examination reveals a clear and sharp regime change for percentage increase in conflict conditional on the observed level of price change following temperature anomalies for rice, sorghum, and millet: the values decrease quickly along the east and west boundaries of Yobe, Borno, and Gombe states, especially across the northern part of the Borno State boundary.

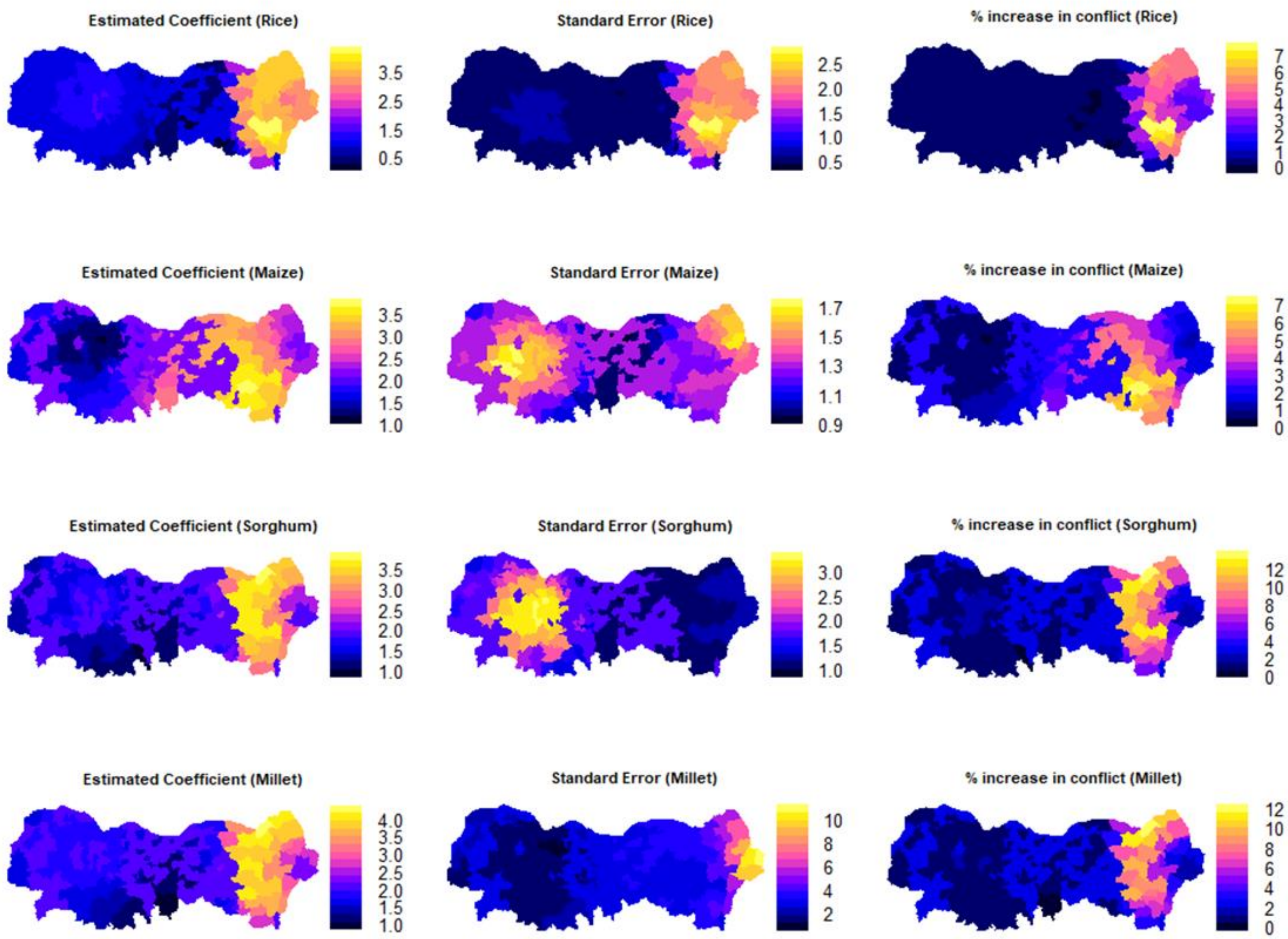

Figure *2* Estimation results (three-month temperature anomalies)

Notes: Estimated coefficient of the interaction term between crop prices and temperature anomaly (left panel for four crops) standard error of the interaction term coefficient (middle panel) and predicted percentage increase in conflict evaluated at the observed level of price change (right panel).

5.2 Observed and anticipatory hotspots of climate insecurity

Having established more confidence in the validity of the localized results and the statistical uncertainty, the district specific parameters are then extracted for selecting observed and anticipatory climate insecurity hotspots. The districts shaded in red and brown colors in Figure A4 in the Appendix show the locations of *observed* climate insecurity hotspots at medium and severe level, respectively. The location of these observed hotspots is largely robust. Conflicts have primarily occurred in the north, which has been plagued by bandit conflicts between the state's government and various militias, as well as herder-farmer conflicts (Chukwuma, 2020). Borno State had the most frequent temperature anomaly during the study period and also most susceptible to price volatilities. As consistent with previous evidence (Last, 2018), observed hotspots exhibit mainly in the eastern part of Sokoto state, where large, forested areas allow for concealment and the formation of camps deep within the forest, which are inaccessible to unprepared police and military personnel.

Figure A5, on the other hand, illustrates the location of *the anticipatory* hotspots, clustering in Bauchi, Jigawa, State and Kano State. Bauchi State is one of the major producers of rice in Nigeria thus it is particularly impacted by abnormal climate conditions. These areas are relatively less conflict-affected if compared to the climate insecurity hotspots but due to their sensitiveness to climate-induced price shocks, they may become future hotspots if adverse climate conditions become more common in these areas.

From Figure 2, Figure A4 and A5, districts that demonstrate high susceptibility to climate-induced market shocks (i.e., larger coefficient of the interaction term between climate shock and agricultural prices) exhibit apparent clustering patterns. This motivates us to overlay hotspots with other layers that policy makers consider important and explore the spatial pattern. Figure A6 displays four important socio-economic and demographic variables measured in the year 2018, including proximity to water (top left), ethnicity diversity (top right), irrigation intensity (bottom left) and urban population (bottom right) compiled from the Demographic and Health Surveys (DHS). The observed climate insecurity hotspots tend to concentrate around regions that are close to water sources and have lower urban population. The former may be linked with resource-driven disputes. Agricultural production is heavily dependent on water resources especially following temperature anomaly, thus proximity to water may induce more climate-related conflict mediated by agricultural price changes. Yet none of the variables alone offers sufficient explanation for the location of hotspots and we find neither clear and linear correlation between the layers and the clustering of conflict nor any significant marginal effect of the interaction term of temperature anomaly and prices.

5.3 Future prospects of climate-related conflict: 2030-2040

Our analysis so far has focused on the impact of past climate variability using historic observations of temperature anomalies. Figure 3 presents the trajectory for three representative districts. The vertical axis in the graphs shows the estimated percentage increase in conflict associated with projected percentage increase in high temperature. Positive number indicates a positive linkage between temperature anomaly and conflict mediated by agricultural prices, as predicted from the model. The Maiduguri district, a current hotspot of climate insecurity located in the Borno State, is expected to experience higher climate-related conflict mediated by agricultural prices, although the percentage increase in conflicts is expected to slow down after 2030. In the Bade district the association between high temperature and conflict is expected to continue to be weak and statistically insignificant, while in Zurmi district such association may increase given future temperature conditions. This exercise showcases that the future climate change conditions should also be taken into account both in projecting the spatial distribution of the climate-conflict associations as well as in framing corresponding prioritization strategy to mitigate climate-related conflicts.

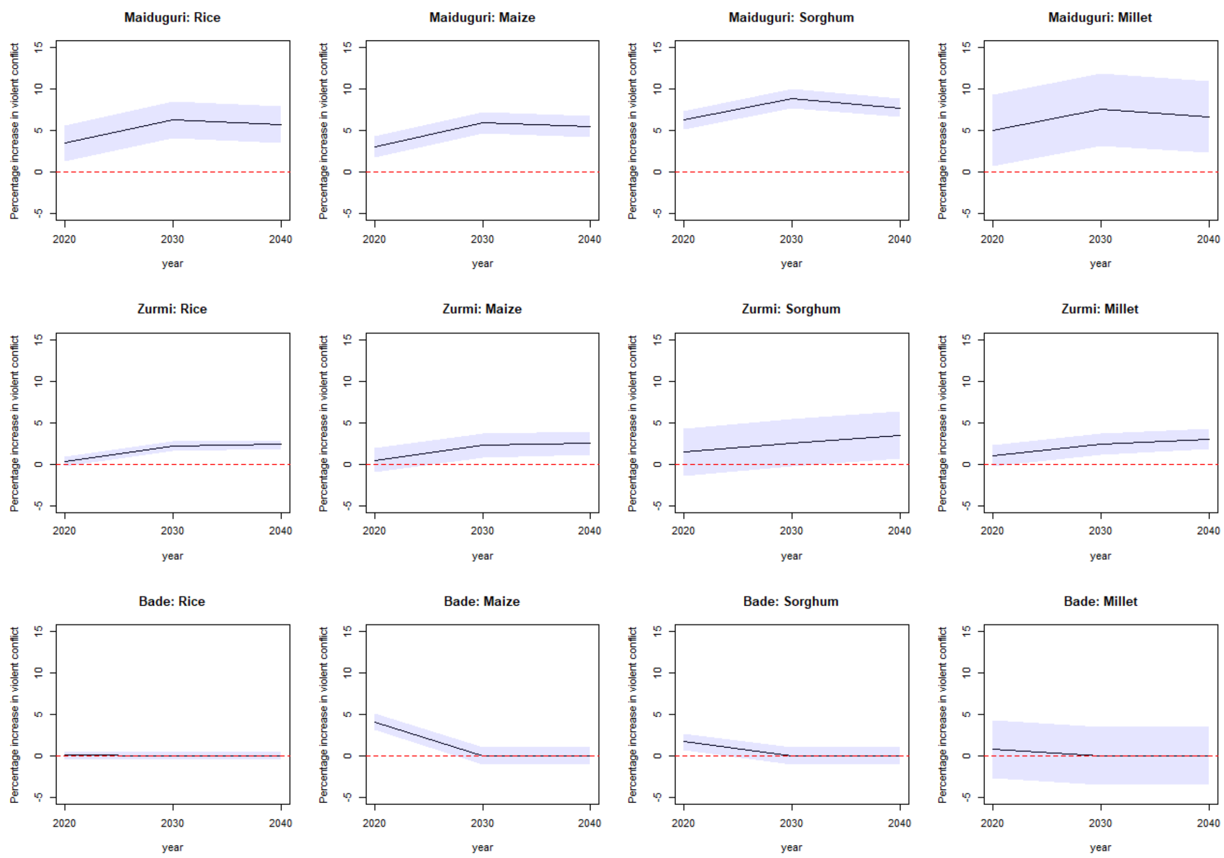

Figure 3. Estimated percentage increase in conflict with future climate conditions.

Notes: Estimated percentage increase in conflict with future climate conditions under RCP 4.5 with 95% confidence intervals. A Representative Concentration Pathway (RCP) is a greenhouse gas concentration trajectory adopted by the IPCC. RCP 4.5 is described by the IPCC as an intermediate scenario. RCP 4.5 is the most probable baseline scenario (no climate policies) taking into account the exhaustible character of non-renewable fuels

5.4 Robustness check and diagnostics

It is possible that the effect of temperature anomaly may have a longer lagged effect on agricultural commodity market and conflict. As the robustness check, we repeat the above estimation using six-month temperature anomalies. The results are reported in Table A1 in the appendix. There is robust and positive association (except for some areas with respect to rice prices and maize prices that have negative coefficients) between price changes and conflict in the face of temperature anomalies. The results confirm that conflict is amplified when crop prices rise following an abnormal maximum temperature episode. Moreover, the effects of six-month temperature anomalies are smaller and tend to be insignificant compared to three-month, suggesting the effect of climate-induced price shock on conflict may be rapid and contemporaneous. On average, at the observed crop price change before and after the temperature anomaly for each crop, the associated conflict increased approximately 3.3% with respect to rice price change, 5.0% with respect to maize price change, 6.6% with respect to sorghum price change, and 3.3% with respect to millet price change.

Figure A6 shows the number of significant local estimates on the permutation based empirical distribution. For all the four crops, the distribution clusters at zero as we expect. For rice and maize, the number of significant local estimates are located at the right end, suggesting the spatial effect we observe is very likely the results of spatial heterogeneity rather than non-linearity or coincidence, or overfitting.

Figure A3 in the Appendix plots the areas where the net marginal effect of the temperature anomaly, conditional on the respective local price level, is positive and significant. In most of the eastern regions, temperature anomalies display a significant harmful net marginal effect. For rice, sorghum, and millet, temperature anomalies exert harmful effects in most eastern regions, including Borno, Yobe, and Niger State.

We further use different bandwidths and different kernel functions in the estimation. The results are largely robust, except that with a Gaussian kernel and fixed bandwidth, the average effect of the interaction term with rice is no longer significant. Moreover, the main specification outperforms these models in terms of AIC. The average fixed bandwidth distance is 75 km. The densities of the local parameters are reported in Figure A8 in the Appendix. Also, since the crop market prices used in this analysis are wholesale crop prices and rising food prices may pose a stronger shock to net consumers, the empirical associations we have discovered so far may be stronger for areas that are likely to be buyers of these crops. Therefore, we repeat the main model shown in Table 1, this time restricting the subsample to only areas that have a crop market. This leaves 37 markets, and the local results are greater than the model using all observations.

6. Conclusion and policy implications

Evidence shows that pressure from climatic shocks may indirectly intensify conflict in vulnerable areas, conditional on several moderating factors, including agricultural commodity prices. In previous studies, such relationships were assumed to be spatially constant or follow the same underlying process. Yet, depending on the extent of spatial disparity among these interrelated factors, the same level of climate shocks at two locations may elicit different degrees of market responses associated with climate-related conflict. To capture this spatial non-stationarity, this study presents a spatially explicit framework that characterizes the current and future climate insecurity landscape in Northern Nigeria, where the complex local contexts challenge the validity of the spatial stationarity assumption.

Through estimating local regressions in the time span examined (2016–2019), we find that temperature anomalies on average exert a harmful effect across northern Nigeria when staple crop prices rise following a temperature anomaly episode, especially in the north-eastern regions, which is significant for rice and maize. The findings imply that the strength of the climate-market-conflict nexus is heterogeneous and that unobserved geopolitical and social-economic factors can condition the effect of agricultural markets in affecting conflict in the face of climate shocks. This is consistent with the evidence that in these areas, in response to environmental deterioration and a lack of water and arable land, communities competed viciously for these limited resources. Unemployment, widespread poverty, and weak local governments have further enabled a steady flow of destitute individuals to engage in criminal activity to make a living. In a vulnerable context with geographical and social-economic fragmentation, where conflicts are concentrated in a few areas and agricultural markets are unevenly distributed, relaxing the assumption of stationarity such that the regional-specific effect is allowed to be driven by the different underlying spatial processes can offer richer insights.

Interestingly, the magnitude of this amplifying effect can exhibit both positive spatial autocorrelation patterns, where neighboring areas show similar susceptibility to climate-related price changes, and negative spatial autocorrelation, where adjacent areas show drastically different sensitivity to such price changes, emphasizing the importance of localized market-related peacebuilding efforts. Temperature anomalies exert significant harmful influences on violence in most regions. Besides the coefficient estimated, visualization of the standard error also provides guidance on the uncertainty of these parameters and on where the estimation results should be interpreted with caution.

From a policy perspective, the evidence generated is expected to support the design and targeting of policies aimed at reducing the surge and the exacerbation of conflicts in the aftermath of temperature anomalies and other extreme weather events. Under limited resources and complex local contexts, identifying hotspots more vulnerable to rising insecurity risks is critical for informing targeted interventions. In particular, the selection of anticipatory hotspots foreshadows a possibility in which regions that are currently not sites for chronic conflict may be potentially redefined as climate-insecure hotspots in the future. For instance, early warning systems may pay greater attention to the level of food prices and target food price stabilization efforts in conflict-vulnerable districts (Minot, 2014).

Looking forward, climate change is anticipated to continue to apply pressure to food systems in the form of production losses that may lead to increases in food prices (Bosello, Campagnolo, & Cervigni, 2018) The distribution of future vulnerability may diverge from its current pattern and the interaction of temporal and spatial heterogeneity complicates the understanding of how climate security landscape might evolve in the future. In fact, climate change scenarios suggest a warmer climate in the future of Nigeria and the location of climate hazard especially temperature anomaly may diverge from current occurrence.

Some caveats should be taken into account regarding the generalizability of the results. First, our spatial heterogeneity analysis offers an explorative presentation of the diverse landscape of climate-related conflicts following temperature anomalies. It is not designed as an explanatory method to unpack the mechanism that generates the dispersion. Relatedly, our empirical model estimates a reduced-form relationship between climate shock and conflicts conditional on crop market prices. Evidence shows that conflict can lead to rising food prices (Anderson, 2021) and hinder staple food supply, compounding challenges for households trying to buy and sell food and livestock (Justino, 2011). Attempts to mitigate the concern on reverse causality include using forwarded conflict variables, proper fixed effects, or IV approach. Yet two stage least squared approach using weather variable as IV may suffer several major limitations outlined in recent study (Mellon, 2022) as extreme weather events rarely operate through only one channel in affecting conflicts. Due to these reasons, we do not attempt to provide a causal interpretation of the price channel through which climate impact on conflict operates, and our estimate represents the moderator role of crop price on climate-conflict relations under certain plausible assumptions. Nonetheless, relaxing the strong exogeneity assumption made in IV estimation and adopt alternative framework such as the causal mediation analysis may improve the validity of estimation and aid in the causal comprehension of climate-conflict nexus, particularly those involving agri-food system channels. Second, one caveat associated with GWR is the repeated use of observations through the moving window of the spatial kernel function at each regression point. Although the risk of over-exploitation of the variability is minimized through careful diagnostics, the sparsity of the data limits the precision of point estimates and goodness of fit. Finally, due to limitations on projected temperature anomaly, we are only able to proxy the future climate shock using projected increase in number of high temperature days, which offers a reasonable approximation of spatial heterogeneity in climate shock frequency in the near term compared to historic period, yet we acknowledge this is not precisely the same as increase in temperature anomalies. We acknowledge that because of these constraints, this study cannot provide a comprehensive picture of the dynamics of prices, temperature anomalies, and conflicts in Northern Nigeria. Additional research would benefit from more complete market data and more information on covariates such as displacement that could exacerbate armed conflict across regions. For these limitations, we consider our depiction of current and future climate security landscape through geographical framework and the hotspots selection as work in progress and encourage practitioners and researchers to contribute.

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Declaration of Interest Statement

The authors declare that they have no conflict of interest.

References

Abidoye, B., & Calì, M. (2021). Income Shocks and Conflict: Evidence from Nigeria. *Journal of African Economies, 30*, 478–507.

Ajala, O. (2020). New drivers of conflict in Nigeria: an analysis of the clashes between farmers and pastoralists. *Third World Quarterly, 41*(12), 2048-2066.

Ajetomobi, J., Ajakaiye, O., & Gbadegesin, A. (2015). The Potential Impact of Climate Change on Nigerian Agriculture. *AGRODEP Working Paper, 0016*, 1–44.

Anderson, W. C.-N. (2021). Violent conflict exacerbated drought-related food insecurity between 2009 and 2019 in sub-Saharan Africa. *Nature Food, 2*(8), 603-615.

Awodola, B., & Oboshi, A. (2015). Terrorism in northern Nigeria: A threat to food security in Maiduguri. *Mediterranean Journal of Social Sciences, 6*(3), 11.

Bandara, J., & Cai, Y. (2014). The impact of climate change on food crop productivity, food prices and food security in South Asia. *Economic Analysis and Policy, 44*(4), 451-465.

Barrios, S., Ouattara, B., & Strobl, E. (2008). The impact of climatic change on agricultural production: Is it different for Africa? *Food policy, 33*(4), 287-298.

Bellemare, M. F. (2015). Rising food prices, food price volatility, and social unrest. *American Journal of Agricultural Economics, 97*(1), 1-21. doi:https://doi.org/10.1093/ajae/aau038

Berazneva, J., & Lee, D. R. (2013). Explaining the African food riots of 2007–2008: An empirical analysis. *Food policy*, 28-39.

Bergquist, L. F., & Dinerstein, M. (2020). Competition and entry in agricultural markets: Experimental evidence from Kenya. *American Economic Review, 110*(12), 3705-3747.

Bosello, F., Campagnolo, L., & Cervigni, R. (2018). Climate change and adaptation: the case of Nigerian agriculture. *Environmental and Resource Economics, 69*(4), 787-810.

Brunsdon, C. (1996). Geographically weighted regression: a method for exploring spatial nonstationarity. *Geographical Analysis, 28*(4), 281-298.

Brunsdon, C., Fotheringham, A. S., & Charlton, M. (2002). Geographically weighted summary statistics—a framework for localised exploratory data analysis. *Computers, Environment and Urban Systems, 26(6), 501-524.*

Bush, R. (2010). Food Riots: Poverty, Power, and Protest. *Journal of Agrarian Change, 10*, 119–129.

Chukwuma, K. H. (2020). Constructing the herder–farmer conflict as (in) security in Nigeria. *African Security, 13*(1), 54-76.

Collier, P. (2007). Africa's economic growth: opportunities and constraints. *African Development Review, 19*(1), 6-25.

Collier, P. C. (2008). Climate change and Africa. *Oxford Review of Economic Policy, 24*(2), 337-353.

Day, A., & Caus, J. (2020). *Conflict Prevention in the Era of Climate Change: Adapting the UN to Climate-Security Risks.* United Nations University Centre for Policy Research.

Ewi, M. A., & Salifu, U. (2017). Money Talks-A Key Reason Youths Join Boko Haram.

Federal Ministry of Environment. (2021). *2050 Long-Term Vision for Nigeria*. Department of Climate Change.

Freeman, L. (2017). Environmental change, migration, and conflict in Africa: a critical examination of the interconnections. *The Journal of Environment & Development, 26*(4), 351-374.

Fudjumdjum, H., Leal Filho, W., & Ayal, D. Y. (2019). Assessment of barriers to food security in North-Eastern Nigeria. In *Handbook of Climate Change Resilience. Cham.* Retrieved from https://doi. org/10.1007/978-3-319-71025-9_99-1

Harari, M., & Ferrara, E. L. (2018). Conflict, climate, and cells: a disaggregated analysis. *Review of Economics and Statistics, 100*(4), 594-608.

Hastings, J. V., Phillips, S. G., & Ubilava, D. (2022). Price transmission in conflict-affected states: evidence from cereal Markets of Somalia. *Journal of African Economies, 31*(3), 272-291.

Ide, T. (2017). Research methods for exploring the links between climate change and conflict. *Wiley Interdisciplinary Reviews: Climate Change, 8*(3), 456.

Justino, P. (2011). Violent conflict and human capital accumulation. *IDS Working Papers, 379*, 1-17.

Kakpo, A., Mills, B. F., & Brunelin, S. (2022). Weather shocks and food price seasonality in Sub-Saharan Africa: Evidence from Niger. *Food Policy, 112*, 102347.

Kamai, N., & Omoigui, L. (2020). Guide to Rice Production in Northern Nigeria. *IITA*,. doi:https://www.iita.org/wp-content/uploads/2020/07/Guide-to-Maize-Production-in-Northern-Nigeria.pdf

Last, M. (2018). The Oxford Handbook of Nigerian Politics. In *From Borno to Sokoto* (p. 19).

Maystadt, J. F., & Ecker, O. (2014). Extreme weather and civil war: Does drought fuel conflict in Somalia through livestock price shocks? *American Journal of Agricultural Economics, 96*(4), 1157-1182.

Mellon, J. (2022). Rain, Rain, Go Away: 192 Potential Exclusion-Restriction Violations for Studies Using Weather as an Instrumental Variable. *Available at SSRN 3715610.*

Minot, N. (2014). Food price volatility in sub-Saharan Africa: Has it really increased? *Food Policy, 45*, 45-56.

Nett, K., & Rüttinger, L. (2017). In *Insurgency, terrorism and organised crime in a warming climate.*

Nextier. (2022). *2022 Annual Review of Nigeria's Violent Conflict Profile.* Nextier.

Olurounbi, R. (2021). *Nigeria: Climate change is driving the cost of jollof rice*. Retrieved from The Africa Report: https://www.theafricareport.com/152280/nigeria-climate-change-is-driving-the-cost-of-jollof-rice/

Raleigh, C., Linke, A., Hegre, H., & Karlsen, J. (2010). Introducing ACLED: An armed conflict location and event dataset: special data feature. *Journal of Peace Research, 47*(5), 651-660.

Schlenker, W., & Lobell, D. B. (2010). Robust negative impacts of climate change on African agriculture. *Environmental Research Letters, 5*(1), 014010.

Storeygard, A. (2016). Farther on down the road: transport costs, trade and urban growth in sub-Saharan Africa. *The Review of economic studies, 83*(3), 1263-1295.

USAID. (2022). *Agriculture and Food Security*. Retrieved April 29, 2023, from USAID: https://idea.usaid.gov/cd/nigeria?comparisonGroup=region

Vesco, P., Kovacic, M., Mistry, M., & Croicu, M. (2021). Climate variability, crop and conflict: Exploring the impacts of spatial concentration in agricultural production. *Journal of Peace Research, 58*(1), 98-113.

Von Uexkull, N. (2014). Sustained drought, vulnerability and civil conflict in Sub-Saharan Africa. *Political Geography, 43*, 16-26.

World Bank. (2021). *Nigeria*. Retrieved from Climate change knowledge portal: https://climateknowledgeportal.worldbank.org/country/nigeria/climate-data-historical

Appendix

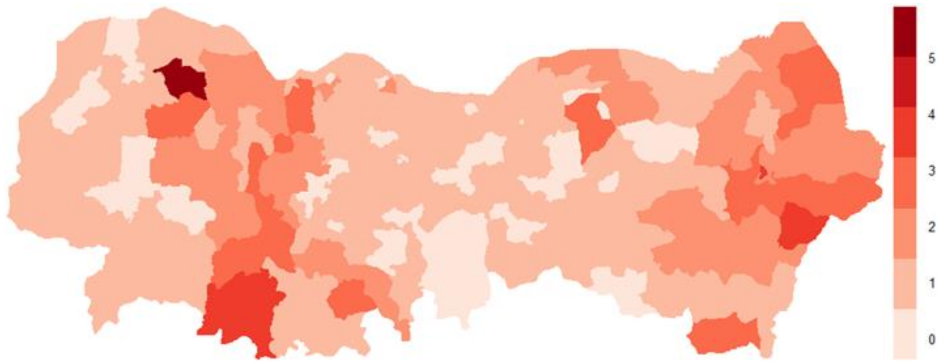

Figure A1. Average number of monthly conflicts 2016-2019

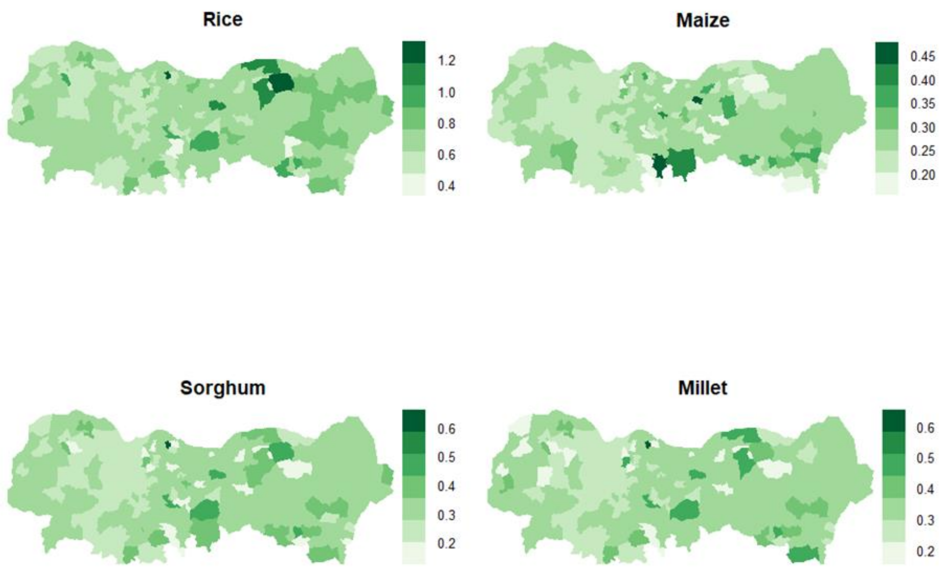

Figure *A2.* Average interpolated agricultural commodity prices

Notes: Price of four major staple crops measured in USD/kg. Rice (top left) maize (top right) sorghum (bottom left) millet (bottom right). All crops are locally produced varieties. Months with prices only available in one market in the northern region are excluded. Maize prices include regular maize, yellow maize, and white maize prices. Sorghum prices include regular sorghum, brown sorghum, and white sorghum.

Table A1. Summary statistics

Variable	Observations	Mean	Std. dev.	Min	Max
Rice price ($/Kg)	1,040	0.71	0.19	0.38	1.62
Maize price ($/Kg)	1,019	0.28	0.09	0.17	0.46
Sorghum price ($/Kg)	934	0.31	0.12	0.15	0.71
Millet price ($/Kg)	985	0.32	0.10	0.17	0.73
Violent conflicts	1,109	1.73	1.80	0.00	15.00
Temperature anomalies 3 month	1,109	0.00	0.61	-1.74	1.75
Temperature anomalies 6 month	1,109	0.01	0.44	-0.94	1.34

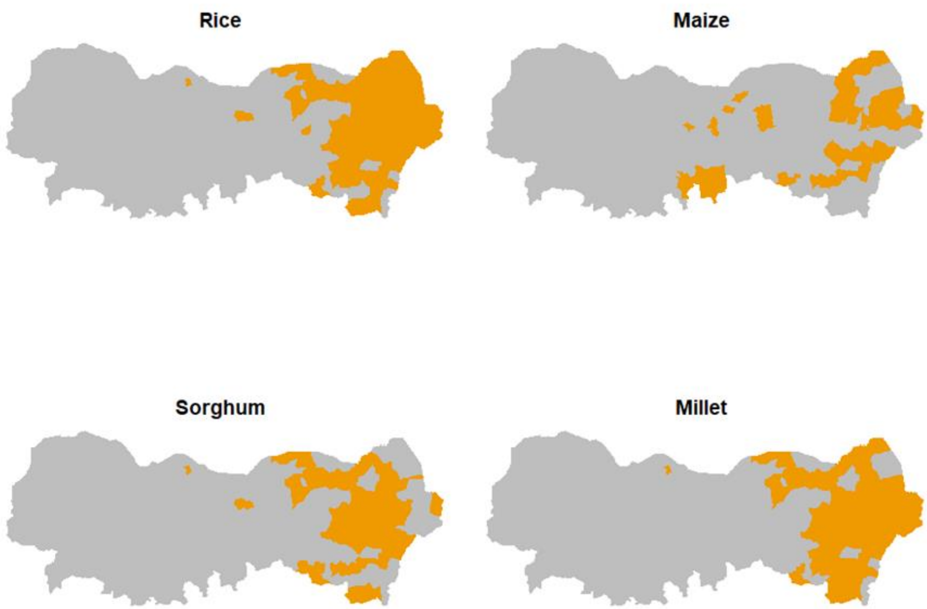

Figure A3. LGAs where temperature anomaly exerts significant and harmful net effects on conflict.

Note: areas where the net marginal effect of temperature anomaly, conditional on respective local price level, is positive and significant. In most of the eastern regions, temperature anomaly displays a harmful net marginal effect.

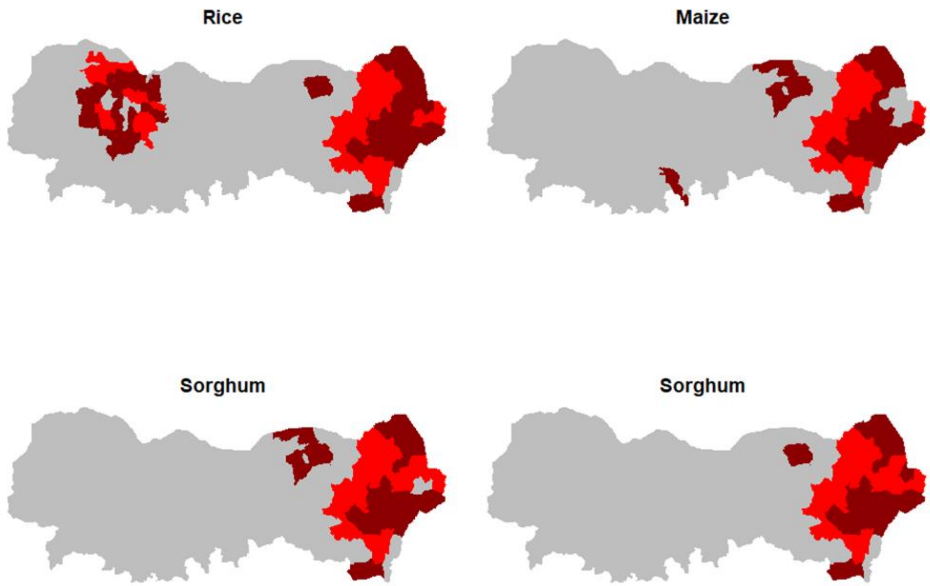

Figure *A4.* Observed climate insecurity hotspots.

Notes: Current climate insecurity hotspots using estimated parameters from the main model. Red spots are LGA that are above the median for both the estimated coefficient of interaction and average monthly conflicts, brown spots are LGA that are above the 75 quantiles for both the estimated coefficient of interaction and average monthly conflicts.

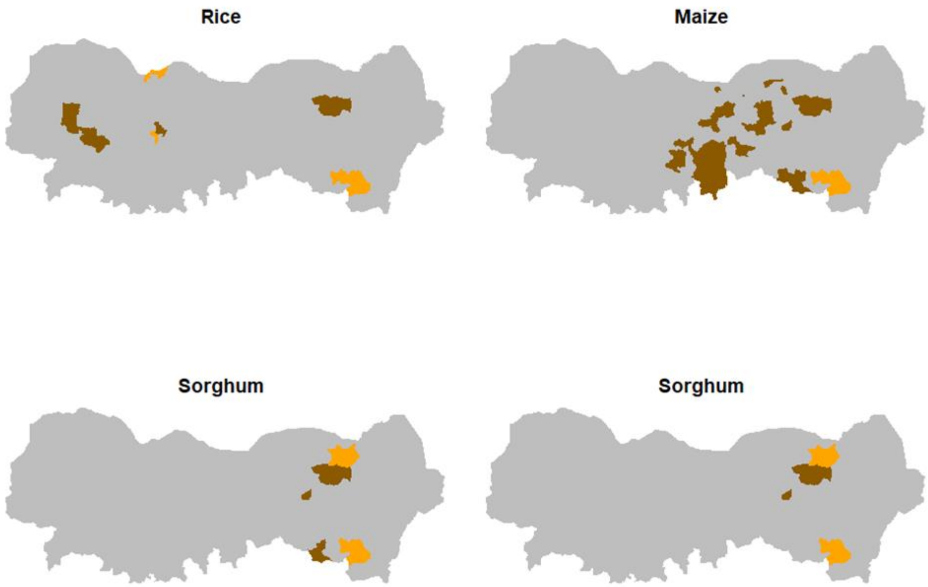

Figure *A5.* Climate insecurity hotspots

Notes: Anticipatory climate insecurity hotspots using estimated parameters from the main model. Orange spots are LGA that are above the median for estimated coefficient of interaction and below median for the average monthly conflicts, brown spots are LGA that are above the 75 quantiles for he estimated coefficient of interaction term and below 25 percentiles of average monthly conflicts.

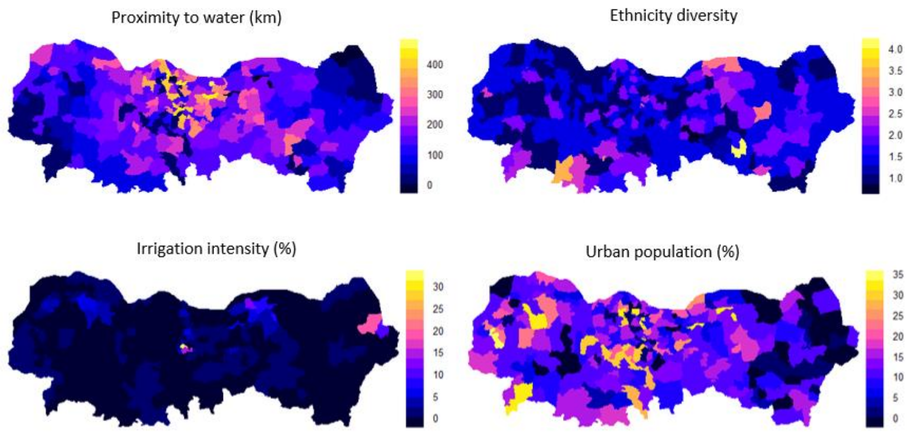

Figure *A6*. Social-economic and demographical characteristics

Notes: socio-economic and demographic variables measured in the year 2018, including proximity to water measured in km (top left), ethnicity diversity measured as standardized number of different ethnicities in each district (top right), irrigation intensity measured as percentage of land covered by irrigation (bottom left) and urban population measured by percentage of urban population in total population (bottom right).

Table *3* Estimation results (six-month temperature anomalies)

	Rice			Maize			Sorghum			Millet		
ESTIMATOR	**Poisson (Global)**	**Poisson (GWR)**		**Poisson (Global)**	**Poisson (GWR)**		**Poisson (Global)**	**Poisson (GWR)**		**Poisson (Global)**	**Poisson (GWR)**	
Three-month Temperature anomaly=1 × Price	0.37	*Min*	-1.1	1.8*	*Min*	-1.69	0.99	*Min*	-0.7	0.97	*Min*	-0.9
		Median	0.39		*Median*	1.27		*Median*	0.07		*Median*	0.15
		Mean	0.4		*Mean*	1.49		*Mean*	0.65		*Mean*	0.5
		Max	1.3		*Max*	1.80		*Max*	1.03		*Max*	1.9
State FE	YES	YES		YES	YES		YES	YES		YES	YES	
Year FE	YES	YES		YES	YES		YES	YES		YES	YES	
Month FE	YES	YES		YES	YES		YES	YES		YES	YES	
Control: maize price	YES	YES		/			YES	YES		YES	YES	
Control: rice price	/	/		YES	YES		YES	YES		YES	YES	
R-square	0.17	0.25		0.17	0.22		0.15	0.20		0.15	0.22	
AIC	1274	1226		1271	1225		1166	1131		1206	1168	
Number of Obs.	951	951		951	951		845	845		896	896	

*Notes: *** p<0.01, ** p<0.05, * p<0.1. Global estimator refers to the Poisson fixed effect model that uses all the data points. The dependent variable is the number of monthly violent conflicts. Exclude months with only one agricultural market information available. Temperature anomaly is a dummy variable equals one if three-month temperature anomaly is above 0. The estimation uses 257 northern LGAs from 13 States. The unit of analysis is LGA-month for both global Poisson fixed effect regression and the GWR Poisson regression estimates. All models include state level fixed effects and month fixed effects. Bandwidth based on cross-validation.*

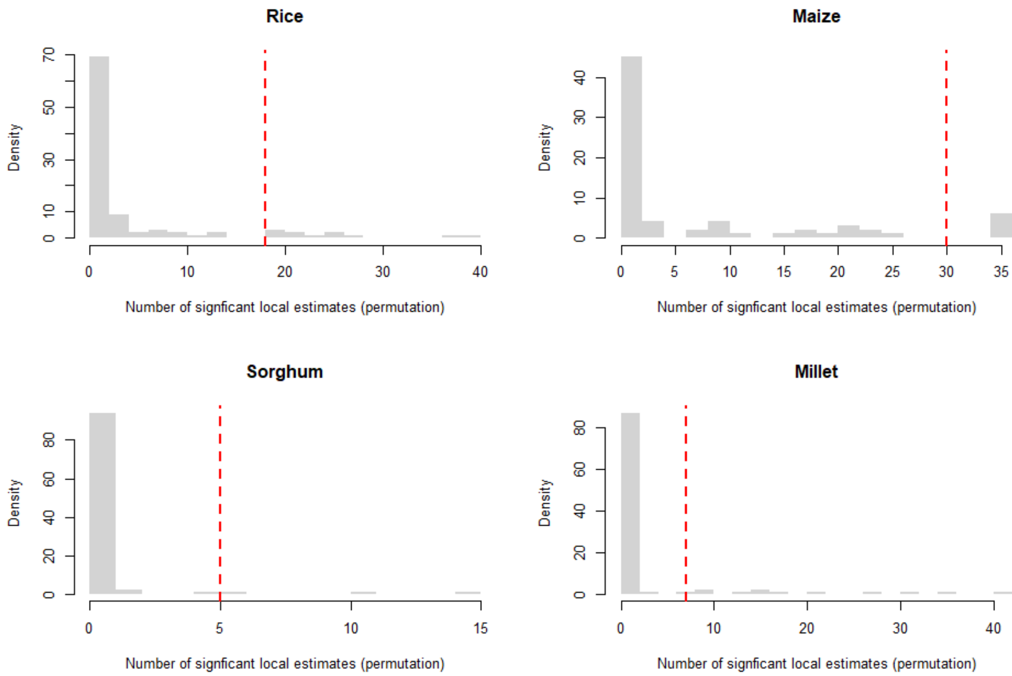

Figure *A7.* Diagnostics of local parameters: number of significant estimates

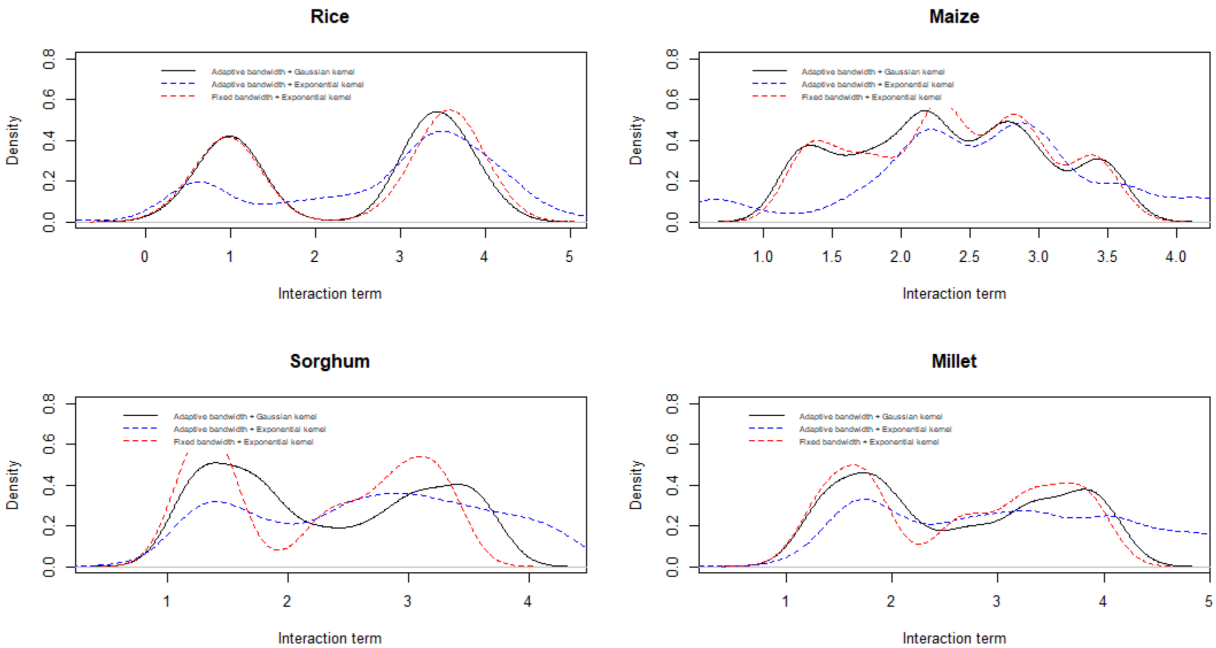

Figure *A8.* Robustness check using different spatial kernels.