Ingénierie des Systèmes d'Information
Vol. 31, No. 10, October, 2026, pp. 3559-3570
Journal homepage: http://iieta.org/journals/isi

Maize Production in East Nusa Tenggara, Indonesia: A Robust Geographically Weighted Panel Regression Analysis

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https://doi.org/10.18280/isi.311026

Received: 13 June 2026
Revised: 4 September 2026
Accepted: 29 September 2026
Available online: 31 October 2026

Keywords:
maize production, geographically weighted panel regression, robust M-estimation, spatial heterogeneity, outlier contamination, Monte Carlo simulation

ABSTRACT

Relationships between maize production and agricultural or climatic conditions can vary across districts, and atypical observations can influence estimates from short regional panels. We applied fixed-effects geographically weighted panel regression (GWPR) with Tukey biweight M-estimation to 88 annual observations from 22 district-level jurisdictions in East Nusa Tenggara (ENT), Indonesia, between 2020 and 2023. The model related total maize production to harvested area, the number of agricultural extension workers, the number of farming households, annual rainfall, and mean annual temperature. We selected location-specific bandwidths by cross-validation and examined estimator sensitivity in Monte Carlo simulations with 500 replications at each of three outlier contamination levels: 10%, 15%, and 20%. Harvested area showed the most consistent association with production: 21 of 22 local estimates were statistically significant at the nominal 5% level. Significant local associations with temperature were found in 10 jurisdictions and included both positive and negative coefficients, whereas rainfall was significant in two. Simulation error increased as the proportion of contaminated observations rose. This pattern describes the sensitivity of the fitted estimator under the specified simulation conditions. The four-year panel limits inference about longer-term changes, and the local coefficients describe conditional associations. The geographic variation in these associations provides a basis for follow-up agronomic assessments of local constraints on maize production.

1. INTRODUCTION

Maize (*Zea mays* L.) is one of the most important cereal crops worldwide, functioning not only as a staple food but also as a major source of animal feed and bioenergy production [1]. Its contribution extends beyond agricultural output, influencing food availability, rural livelihoods, and economic resilience across both developed and developing countries. In Indonesia, maize occupies a particularly strategic position because it serves as the second most important source of carbohydrates after rice while simultaneously supporting the rapidly growing livestock sector [2]. As a result, maize production is closely linked to national food security objectives and broader efforts to achieve food sovereignty. The significance of maize is therefore not merely agricultural but also socio-economic, as fluctuations in maize production can directly affect household welfare, food accessibility, and market stability [3].

Despite its strategic role, maintaining a balance between maize supply and demand remains a persistent challenge in Indonesia. National statistics indicate that maize production has generally increased over the last decade; however, this growth has not consistently matched rising domestic demand [4]. Consequently, dependence on external supply sources remains a concern, exposing the national food system to volatility in global commodity markets and international trade disruptions [5]. Such dependence represents a structural vulnerability because fluctuations in global maize prices or restrictions in international trade can immediately affect domestic availability and affordability. Strengthening local production capacity has therefore become a critical component of Indonesia's food security strategy. Achieving this objective requires a deeper understanding of the factors that drive maize production across different geographical and environmental contexts, particularly in regions where maize serves both as a staple food and as a major source of income.

East Nusa Tenggara (ENT) represents one of the most relevant regions for examining these issues. Unlike many provinces in Indonesia where rice dominates food consumption, maize remains an important staple food for a

substantial proportion of the population. At the same time, the province faces considerable environmental and socio-economic challenges. Its semi-arid climate makes agricultural production highly sensitive to rainfall variability and prolonged drought events, many of which are associated with recurring El Niño phenomena. These climatic conditions frequently lead to production instability and increase the vulnerability of local food systems. Furthermore, substantial disparities in land availability, irrigation infrastructure, farming resources, and institutional support exist across districts, generating pronounced differences in agricultural productivity. Such conditions create a highly heterogeneous agricultural landscape in which production dynamics vary considerably across both space and time. Consequently, understanding the determinants of maize production in ENT requires analytical approaches capable of capturing these spatially and temporally varying relationships.

From a methodological perspective, modeling agricultural production under heterogeneous conditions remains a challenging task. Conventional econometric approaches such as ordinary least squares (OLS) regression and classical panel data models generally assume that the relationship between explanatory variables and agricultural output is spatially homogeneous [6]. Under this assumption, estimated parameters are considered constant across all locations. However, agricultural systems rarely behave in such a uniform manner. Variations in ecological conditions, climate exposure, farming practices, infrastructure availability, and institutional capacity often generate location-specific responses to the same explanatory variables. As a consequence, global models may mask important local variations, resulting in biased estimates and limiting the usefulness of findings for regional policy development. These limitations have motivated growing interest in spatially explicit analytical approaches capable of accommodating geographical heterogeneity.

Advances in spatial data analytics have provided several methodological alternatives for addressing this challenge. Among them, geographically weighted regression (GWR) has emerged as one of the most widely used approaches for analyzing spatially varying relationships because it allows model coefficients to vary across locations [7]. By estimating local parameters rather than a single global coefficient, GWR enables researchers to identify context-specific determinants and generate more geographically relevant insights. This capability has made GWR particularly attractive for studies involving environmental systems, agricultural productivity, land-use dynamics, and regional development.

Nevertheless, agricultural production is inherently a spatio-temporal process. Changes in climate conditions, technological adoption, market structures, and farming practices occur over time and interact with geographical factors in complex ways. Consequently, purely spatial models are often insufficient for capturing the dynamic nature of agricultural systems. To address this limitation, geographically weighted panel regression (GWPR) was developed as an extension of GWR that incorporates both spatial and temporal dimensions simultaneously [8, 9]. By integrating longitudinal information into local regression analysis, GWPR provides a more comprehensive framework for understanding spatially varying processes that evolve over time. This capability makes GWPR particularly suitable for investigating agricultural production systems characterized by strong spatial heterogeneity and temporal variability.

The application of geographically weighted approaches in agricultural studies has produced promising results. Previous studies have demonstrated the usefulness of these methods for investigating crop productivity, environmental influences, and regional agricultural performance. For example, Mondiana et al. [10] successfully applied a geographically weighted framework to analyze sugarcane productivity in East Java and showed that local parameter estimation generated more informative results than conventional global models. Similarly, Cai et al. [8] demonstrated that incorporating both spatial and temporal variability substantially improves the understanding of weather-related impacts on crop production. Collectively, these studies indicate that geographically weighted approaches provide valuable insights into complex agricultural systems that cannot be adequately explained using traditional econometric methods.

However, several important limitations remain within the existing literature. First, although spatial heterogeneity has received considerable attention, relatively little emphasis has been placed on the robustness of geographically weighted models when agricultural datasets contain anomalous observations. Agricultural data are frequently affected by measurement errors, reporting inconsistencies, and extreme climatic events that generate outliers. Because local estimation procedures are particularly sensitive to such observations, the reliability of parameter estimates may be compromised if robustness issues are not properly addressed. Second, empirical applications of robust GWPR remain limited, especially in the context of maize production systems. Existing studies have predominantly focused on yield estimation or climate-response analysis, leaving substantial uncertainty regarding the performance of robust geographically weighted approaches under contaminated data conditions. Third, despite the increasing importance of food security, limited research has integrated robust spatio-temporal modeling frameworks with food security assessment at a localized scale. Most existing studies rely on aggregated regional analyses that overlook district-level production dynamics and fail to provide sufficiently detailed evidence for designing location-specific interventions.

These limitations reveal a focused research gap. Although GWR and GWPR are established tools for representing spatially varying relationships, robust estimation within panel-based geographically weighted agricultural applications remains comparatively limited. M-estimation itself is not new; the contribution of this study is its adaptation within a fixed-effect GWPR workflow for district-level maize production and its evaluation under controlled contamination scenarios. The study therefore emphasizes application, estimator stability, and local coefficient variation rather than claiming a new class of robust estimators.

To address these gaps, this study proposes the application of GWPR with robust M-estimation to analyze maize production across districts in ENT. Unlike previous studies that primarily focus on estimating local relationships, this research explicitly incorporates robustness against data contamination and evaluates estimator performance through simulation experiments under different levels of outlier contamination. In doing so, the study not only investigates the spatially varying determinants of maize production but also assesses the stability and reliability of the proposed modeling framework under realistic agricultural data conditions.

The contribution of this research is threefold. First, it applies established robust M-estimation within a fixed-effect GWPR framework so that spatially varying panel relationships

can be estimated while limiting the influence of atypical residuals. Second, it evaluates estimator stability through 500-replication simulations at 10%, 15%, and 20% contamination. Third, it provides a district-level application to maize production in ENT. These contributions represent a methodological adaptation and empirical evaluation rather than the invention of M-estimation itself.

Accordingly, the objectives of this study are: (i) to apply robust fixed-effects GWPR to maize production in ENT; (ii) to identify geographically varying associations of harvested area, agricultural extension workers, farming households, rainfall, and temperature with maize production; and (iii) to evaluate estimator stability under increasing contamination. Because the observational model does not identify causal effects, the resulting local patterns are discussed as potential evidence for geographically differentiated agricultural assessment rather than as direct prescriptions for intervention.

2. LITERATURE REVIEW

2.1 Food security and agricultural production analytics

Food security has evolved from a production-oriented concept into a multidimensional framework encompassing food availability, accessibility, utilization, and stability. Recent studies emphasize that agricultural production remains a critical component of food security, particularly in developing countries where domestic crop output strongly influences food availability and rural livelihoods. Chen and Yu [11] demonstrated that agricultural development and urban-rural integration significantly contribute to food security outcomes, while Abdullah et al. [12] show that political stability and agricultural foreign direct investment generate both direct and spatial spillover effects on food security. Similarly, Li and Hu [13], Yu and Liang [14], and Zheng and Liao [15] highlighted that food security is increasingly shaped by spatially interconnected agricultural, environmental, and socioeconomic processes.

Although these studies provide important insights into the determinants of food security, most analyses rely on global panel approaches that assume homogeneous responses across regions. Such assumptions may obscure local variations in agricultural production systems, particularly in geographically heterogeneous regions. Consequently, recent literature increasingly calls for spatially explicit analytical frameworks capable of capturing localized production dynamics and supporting evidence-based food security policies.

2.2 Spatial heterogeneity in agricultural and regional systems

Spatial heterogeneity constitutes one of the central challenges in agricultural and regional analysis. Theoretical foundations for addressing this issue were established through the development of GWR, which allows model parameters to vary geographically rather than assuming a single global relationship [7, 16]. The rationale underlying GWR is that socioeconomic, environmental, and agricultural processes are rarely spatially stationary.

Empirical studies demonstrate the broader methodological value of geographically weighted approaches for capturing localized relationships. Cho et al. [17] applied locally weighted regression to rural economic development, while Partridge et al. [18] examined regional growth dynamics across the United States. Other applications include haze pollution [19], agricultural carbon emissions [20], heavy-metal contamination in agricultural soils [21], and household expenditure on safe drinking water [22].

In agricultural systems specifically, Evans et al. [23] demonstrated the usefulness of geographically weighted approaches for analyzing large-scale on-farm experiments, while Fan et al. [24] revealed significant spatial differentiation in agricultural supply-chain performance. More recently, Liu et al. [25] employed GWR to investigate grain production resilience, confirming that agricultural determinants vary substantially across regions. These studies collectively suggest that localized analytical frameworks provide richer insights than conventional global models when agricultural systems exhibit strong spatial heterogeneity.

Nevertheless, GWR remains fundamentally cross-sectional, limiting its ability to capture temporal changes that are intrinsic to agricultural production processes.

2.3 From geographically weighted regression to geographically weighted panel regression

Recognizing the limitations of purely spatial models, Yu [9] introduced GWPR as an extension of GWR that simultaneously incorporates spatial and temporal dimensions. The theoretical formulation was subsequently elaborated by Bruna and Yu [26], establishing GWPR as a framework capable of modeling location-specific relationships while accounting for longitudinal variation.

The ability of GWPR to capture spatio-temporal heterogeneity has motivated applications across multiple disciplines. Cai et al. [8] applied GWPR to weather-related variation in corn yields, providing a direct agricultural example. By contrast, Yu et al. [27] used GWPR to evaluate high-speed rail and county development in China, illustrating the flexibility of the framework beyond agricultural applications. Other applications include poverty, environmental quality, epidemiological, and demographic analyses [28-34].

Recent agricultural studies further reinforce the importance of spatio-temporal approaches. Yang et al. [35] show that climate change impacts on corn yields vary across both space and time, while Dang et al. [36] demonstrated substantial spatio-temporal heterogeneity in agricultural carbon emissions. Similarly, Chen et al. [37] reveal significant spatial spillover effects in agricultural economic resilience. These findings suggest that agricultural systems are inherently dynamic and geographically differentiated, making GWPR a particularly appropriate framework for agricultural analytics.

However, most existing GWPR applications focus on local parameter estimation and explanatory analysis, while limited attention has been given to estimator robustness under contaminated data conditions.

2.4 Robust geographically weighted regression and outlier handling

One of the major methodological challenges in spatial analytics concerns sensitivity to outliers and anomalous observations. Agricultural datasets are particularly susceptible to measurement errors, reporting inconsistencies, missing observations, and extreme climatic events, all of which may distort parameter estimates.

To address this issue, several robust geographically weighted approaches have been developed. Qu et al. [38] proposed the robust geographically weighted regression (RGWR) framework to improve source apportionment of soil contaminants. Sugasawa and Murakami [39] introduced adaptive RGWR, demonstrating improved estimator stability in the presence of outliers. More recently, Setyowati et al. [40] evaluated robust estimators for district-level stunting analysis and found that robust procedures substantially improve estimation reliability.

Within the GWPR literature, Mondiana et al. [10] integrated M-estimation into a fixed-effect GWPR framework to estimate sugarcane productivity in East Java, providing empirical evidence that robust estimation can improve model performance under contaminated agricultural data conditions. These developments indicate a growing recognition that robust estimation should be considered an essential component of spatially weighted models rather than a supplementary adjustment.

Despite these advances, empirical evidence regarding the robustness behavior of GWPR under systematically controlled contamination scenarios remains limited. Existing studies generally emphasize model estimation and prediction accuracy while providing relatively little discussion regarding estimator stability and robustness performance.

2.5 Research gap and scientific contribution

The literature reviewed above reveals several important gaps.

First, although spatial heterogeneity has been widely documented in agricultural systems, many food security and agricultural production studies continue to rely on globally estimated models that may overlook localized production dynamics [11-13].

Second, while GWPR has emerged as a powerful framework for modeling spatio-temporal heterogeneity [8, 9, 26], empirical applications remain concentrated on parameter estimation and prediction, with limited investigation of estimator robustness under contaminated data conditions.

Third, although robust geographically weighted methods have shown promising results [10, 38, 39], few studies have systematically evaluated robustness performance through simulation-based contamination experiments, particularly within agricultural production systems.

Finally, district-level evidence on robust spatio-temporal modeling of maize production remains limited in climate-vulnerable regions. Although maize production is relevant to food availability, the present study does not directly model multidimensional food-security outcomes such as access, utilization, or stability.

Accordingly, this study applies robust GWPR based on M-estimation and evaluates estimator behavior under multiple contamination scenarios. The contribution is deliberately bounded to methodological adaptation, reproducibility, estimator stability, and district-level variation in maize-production associations rather than a broad scientific-computing or multidimensional food-security analysis.

3. METHOD

This study was conducted in 22 districts of ENT, Indonesia, over 2020–2023, forming a balanced panel of 88 district-year observations (22 districts × 4 years). The four-year period is sufficient for the present short-panel application but does not support claims about long-term agricultural trends. Annual district data were compiled from official BPS-Statistics Indonesia (BPS) and Meteorology, Climatology, and Geophysics Agency (BMKG) sources. Production and agricultural variables were harmonized by district and year before panel construction, while rainfall and temperature were matched to the corresponding annual district observations. The analysis uses complete district-year records in the assembled panel. Maize production, harvested area, number of farming households, and number of agricultural extension workers were taken from the annual BPS publications Provinsi Nusa Tenggara Timur Dalam Angka (2021–2024 editions, agriculture chapter) and the corresponding district-level BPS releases for the reference years 2020–2023. Annual rainfall and mean annual temperature were compiled from BMKG climate-station records accessed through the BMKG Online Data Center (https://dataonline.bmkg.go.id); monthly station observations were aggregated to annual district values (total annual rainfall and mean annual temperature) using the BMKG station located in or nearest to each district.

The dependent variable in this study is maize production (Y), measured as the total output (in tons) per district per year. Five explanatory variables were included to capture both production and environmental determinants. The first variable, harvested area of maize (X_1), measured in hectares, reflects the scale of land devoted to cultivation. The second, number of agricultural extension workers (X_2), expressed in persons, represents institutional and technical support for farmers. The third, number of farming households (X_3), measured in households, indicates the participation of rural labor in maize cultivation. Two climate-related variables were also considered: annual rainfall (X_4) in millimeters and mean annual temperature (X_5) in degrees Celsius.

Together, these variables capture the key dimensions influencing maize production in ENT [41]. Harvested area represents production scale, extension workers provide institutional support, and farming households reflect the labor base. Meanwhile, rainfall and temperature function as critical climate drivers in semi-arid systems. The inclusion of these factors is theoretically justified, as they are closely linked to maize productivity and regional food security, particularly in a region like ENT where agricultural performance is highly sensitive to both biophysical conditions and institutional support.

The analytical procedure is summarized below. Spatial weights are constructed using an adaptive Gaussian kernel, consistent with Eq. (4), and location-specific bandwidths are selected by minimizing the cross-validation (CV) criterion in Eq. (3). Robust estimation is performed by iteratively reweighted least squares (IRLS) using the Tukey biweight M-estimator, with robust weights defined as $w_i = (1 - u_i^2)^2$ for $|u_i| < 1$ and $w_i = 0$ otherwise, where $u_i = e_i/(4.685)$ for standardized residuals. The tuning constant is set to 4.685, with a numerical convergence tolerance of 10^{-4} and a maximum of 1,000 IRLS iterations. The analysis is implemented in R using the MASS, dplyr, plm, sp, spdep, sf, readxl, openxlsx, writexl, ggplot2, and magrittr packages.

1. Describing the data using a heatmap and boxplot.
2. Perform the Breusch–Pagan test as a diagnostic for heteroskedasticity in the global regression residuals.

The Breusch–Pagan test evaluates whether the conditional variance of the global-model errors is constant. The null

hypothesis is homoskedasticity, H0: $\mathrm{Var}(\varepsilon|X) = \sigma^2$, whereas the alternative is non-constant error variance. Rejection of H0 is evidence of heteroskedasticity, not by itself evidence of spatial autocorrelation. Spatial dependence is therefore assessed separately using global Moran's *I* on the global-model residuals.

H0: $\mathrm{Var}(\varepsilon|X) = \sigma^2$ (constant error variance).

H1: $\mathrm{Var}(\varepsilon|X)$ is not constant for at least part of the sample.

The Breusch–Pagan statistic is computed as follows:

$$BP = \left(\frac{1}{2}\right) h^T (Z^T Z)^{-1} Z^T \sim \chi^2_{p+1} \quad (1)$$

where, *h* is the transformed squared-residual vector and *Z* is the matrix of variables used in the auxiliary variance regression.

The decision rule is based on the corresponding chi-square reference distribution at the selected significance level.

To assess residual spatial autocorrelation, global Moran's *I* is calculated using a prespecified spatial-weights matrix *W*. Positive and statistically significant Moran's *I* indicates clustering of similar residuals, whereas a non-significant result indicates no detectable global residual spatial autocorrelation under the selected *W*.

$$I = \frac{n}{S_0} \cdot \frac{\Sigma_i \Sigma_j w_{ij}(e_i - \bar{e})(e_j - \bar{e})}{\Sigma_i (e_i - \bar{e})^2}$$

3. Detect potentially influential observations using the boxplot/interquartile range (IQR) diagnostic as an exploratory screen. Because an extreme district value may reflect genuine agricultural structure rather than error, observations are not automatically deleted; robustness is handled through the M-estimation weights.

4. Construct the geographical weighting component of the GWPR model.

•Obtain the longitude and latitude coordinates for each district centroid or representative location.

•Calculate the Euclidean distance (d_{ij}) between locations *i* and *j*:

$$d_{ij} = \sqrt{(u_i - u_j)^2 + (v_i - v_j)^2} \quad (2)$$

•Select the location-specific bandwidth by minimizing the CV criterion:

$$\mathrm{CV}(h) = \sum_{i=1}^{n} (y_i - \hat{y}_{i \neq 1})^2 \quad (3)$$

•Calculate the adaptive Gaussian spatial weight matrix. For location *i*, the weight assigned to observation *j* is:

$$w_{ij} = \exp\left(-\frac{1}{2}\left(\frac{d_{ij}}{h_i}\right)^2 \right) \quad (4)$$

5. Estimate the fixed-effect GWPR model using robust M-estimation through IRLS:

•Apply the within (demeaning) transformation to remove time-invariant district fixed effects.

•Obtain an initial geographically weighted estimate $\beta^{(0)}$ and the corresponding residuals $e_i^{(0)}$.

•Estimate a robust residual scale using the median absolute deviation (MAD), with the 1.4826 consistency factor.

•Standardize the residuals as $u_i = e_i/s$, where s denotes the robust scale estimate.

•Compute robust residual weights from the M-estimator score function $\psi(\cdot)$:

$$w_i^*(u_i)^{(0)} = \frac{\psi(u_i)^{(0)}}{u_i{}^{(0)}} \quad (5)$$

•Combine the geographical and robust residual weights and update the coefficient vector by weighted least squares:

$$\widehat{\beta_M} = (X^T W^m X)^{-1} X^T W^m y$$

•Recompute residuals and robust weights after each coefficient update.

•Repeat the IRLS updates until the coefficient change satisfies the prespecified convergence tolerance or the maximum number of iterations is reached.

6. The Monte Carlo simulation study is conducted as follows:

•Treat the coefficient estimates obtained from the empirical robust GWPR fit as the reference parameter vector β^0 for the simulation. This definition should be used consistently when computing simulation bias.

•For each replication, generate a fresh stochastic error vector from the distribution used in the computational experiment and independently select the observations to be contaminated at proportions of 10%, 15%, and 20%. Each contamination scenario is repeated 500 times.

•Generate the simulated response using the five explanatory variables included in the empirical model and the reference parameter vector:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 X_{5i} + \varepsilon_i \quad (6)$$

- Re-estimate the model for each contaminated dataset using the same robust GWPR specification and convergence settings as in the empirical analysis.
- Evaluate estimator performance using Bias and Mean Squared Error (MSE) across the 500 replications. Because the reported simulation results provide Bias and MSE but no AIC values, AIC is removed from the simulation-performance description. Let R = 500 and θ^0 denote the reference parameter.

$$\mathrm{Bias}(\theta) = (1/R)\Sigma_{r=1}{}^{R}(\theta_r - \theta^0)$$

$$\mathrm{MSE}(\theta) = (1/R)\Sigma_{r=1}{}^{R}(\theta_r - \theta^0)^2$$

4. RESULTS AND DISCUSSION

Figure 1 presents the spatial distribution of maize production in ENT for the years 2020–2023. The heatmaps reveal clear spatial disparities, with production concentrated in specific districts while others recorded relatively low outputs.

Districts with consistently high maize production are highlighted in the purple to green color range. These include East Flores (Flores Timur), East Sumba (Sumba Timur), and South Central Timor (Timor Tengah Selatan), which appear as the main contributors across the four years. On the other hand, districts such as Manggarai, West Manggarai, and Alor,

displayed in orange to red colors, recorded low production levels throughout the observed period.

In 2022, the concentration of production became more pronounced, with East Sumba and South Central Timor remaining in the purple-green categories, confirming their dominance in maize production. Meanwhile, most districts in the western islands of ENT were shown in orange–red shades, indicating relatively small contributions.

Overall, the heatmaps indicate that maize production in ENT is spatially concentrated, with only a few districts achieving high output (purple–green, above 120,000 tons), while many areas remain in the low production range (orange–red, below 40,000 tons). This uneven distribution highlights the importance of adopting spatially explicit models to capture the determinants of maize production across districts.

The results of the Breusch–Pagan heteroskedasticity diagnostic are shown in Table 1; residual spatial autocorrelation is assessed separately using global Moran's *I*.

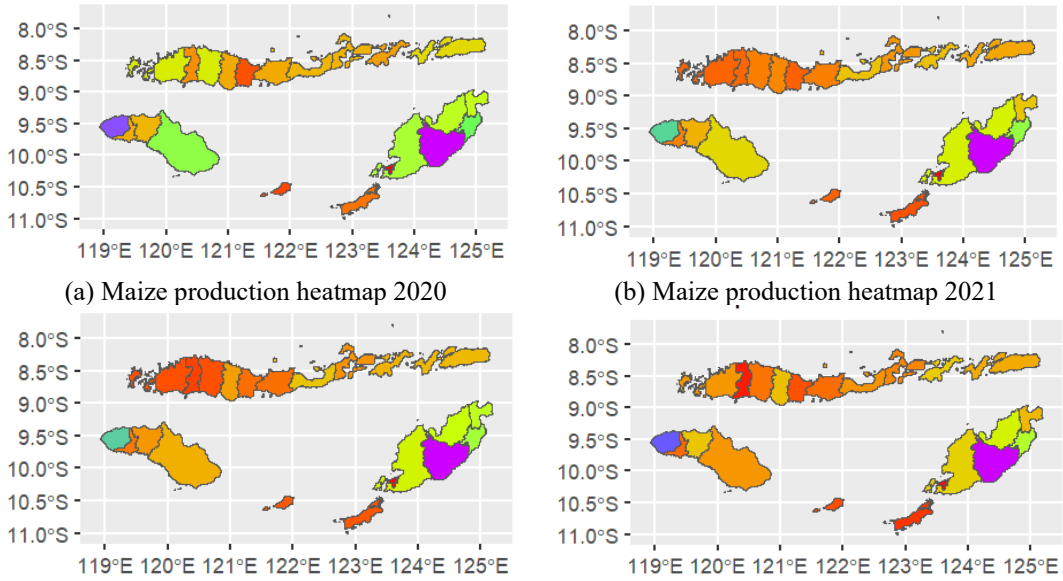
As presented in Table 1, the Breusch–Pagan statistic was 4.44 with a *p*-value of 0.003. Because the *p*-value was below the 0.05 significance level, the null hypothesis of constant residual variance was rejected, indicating heteroskedasticity in the global regression residuals. This finding suggests that the residual variance is not constant across observations; however, it should not be interpreted as direct evidence of spatial autocorrelation.

Residual spatial dependence was therefore examined separately using global Moran's *I*. In 2020, Moran's *I* was positive ($I = 0.190$), indicating a tendency toward positive spatial clustering of residuals. However, this pattern was not statistically significant ($z = 1.092$, $p = 0.275$). Thus, there was insufficient evidence to conclude that residuals were spatially autocorrelated in 2020.

For 2021, global Moran's I was negative ($I = -0.195$), with $z = -0.569$ and $p = 0.569$. Although the negative coefficient indicates a tendency for neighboring areas to exhibit dissimilar residual values, the result was not statistically significant. Consequently, the null hypothesis of spatial randomness could not be rejected.

A similar result was observed in 2022. The Moran's *I* statistic was close to zero ($I = 0.049$), with $z = 0.476$ and $p = 0.634$, indicating no statistically significant spatial autocorrelation in the global-model residuals. In 2023, Moran's *I* was again negative ($I = -0.180$), but the corresponding *z*-value of −0.721 and *p*-value of 0.471 indicated that this pattern was also statistically insignificant.

Overall, the global Moran's *I* results consistently failed to reject the null hypothesis of spatial randomness at $\alpha = 0.05$ for all four observation years. Thus, no statistically significant residual spatial autocorrelation remained after estimation of the global panel model for 2020–2023. In contrast, the significant Breusch–Pagan result indicates that heteroskedasticity remains present in the residuals. These diagnostics therefore describe two distinct characteristics of the model residuals: the Breusch–Pagan test provides evidence of non-constant residual variance, whereas the global Moran's *I* tests do not provide evidence of systematic residual spatial dependence. The next step is to provide a descriptive overview of the data using boxplots. Figure 2 presents the boxplots of maize production in ENT for the period 2020–2023.



(a) Maize production heatmap 2020

(b) Maize production heatmap 2021

(c) Maize production heatmap 2022

(d) Maize production heatmap 2023

Figure 1. Heatmaps of maize production in East Nusa Tenggara (ENT), 2020–2023

Table 1. Global-model diagnostic results

Diagnostic	Statistic / *p*-Value	Decision
Breusch–Pagan (BP)	BP = 4.44; $p = 0.003$	Reject H_0
Global Moran's *I* (2020)	$I = 0.190$; $E(I) = -0.059$; $z = 1.092$; $p = 0.275$	Fail to reject H_0
Global Moran's *I* (2021)	$I = -0.195$; $E(I) = -0.059$; $z = -0.569$; $p = 0.569$	Fail to reject H_0
Global Moran's *I* (2022)	$I = 0.049$; $E(I) = -0.059$; $z = 0.476$; $p = 0.634$	Fail to reject H_0
Global Moran's *I* (2023)	$I = -0.180$; $E(I) = -0.059$; $z = -0.721$; $p = 0.471$	Fail to reject H_0

Note: The Breusch–Pagan test evaluates heteroskedasticity in the global regression residuals. At $\alpha = 0.05$, $p < 0.05$ leads to rejection of the null hypothesis (H_0) of constant variance. Global Moran's *I* was calculated separately for each year using a row-standardized Queen contiguity spatial-weights matrix. $E(I)$ denotes the expected value of Moran's I under the null hypothesis of spatial randomness. Four regions had no contiguous neighbors and were excluded from the effective Moran's *I* calculation, resulting in an effective sample of 18 spatial units.

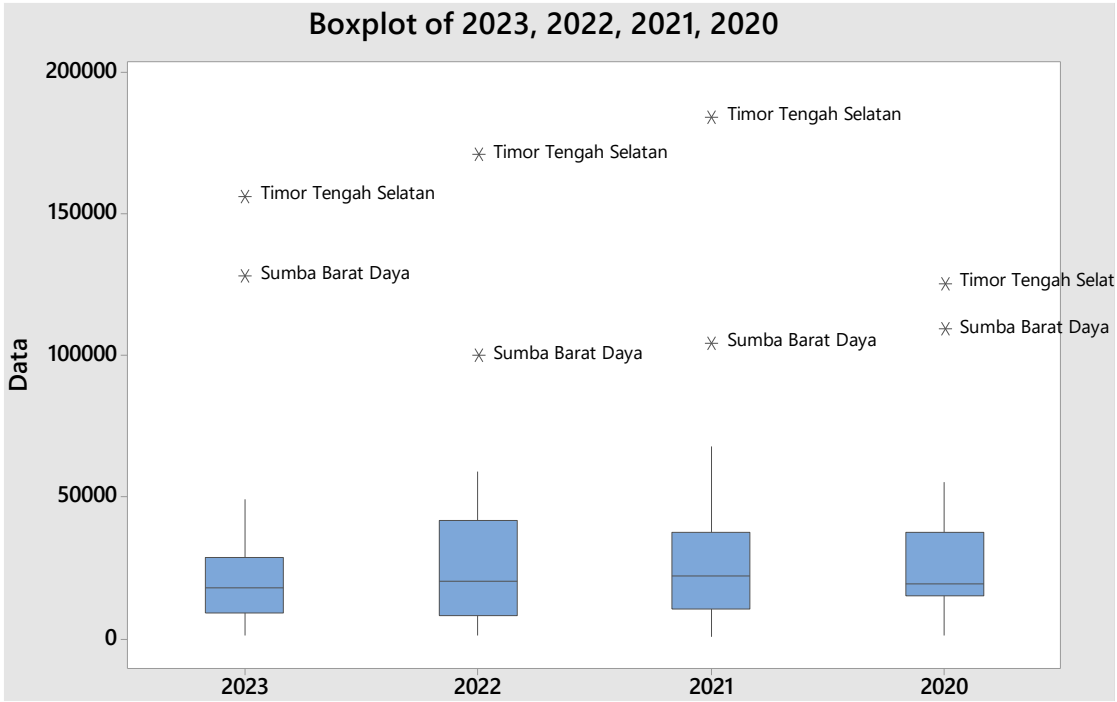


Figure 2. Boxplots of maize production in East Nusa Tenggara (ENT), 2020–2023

The boxplots of maize production across districts in ENT for the years 2020–2023 reveal substantial variability and the presence of extreme observations. For the majority of districts, IQRs are relatively compact, indicating that most production values cluster around the median. However, several districts—most notably Timor Tengah Selatan and Sumba Barat Daya—consistently appear as outliers with production levels far exceeding the upper whiskers. This pattern is evident across multiple years, suggesting structural disparities in agricultural capacity and productivity between districts rather than random fluctuations.

The persistence of these outliers has important methodological implications. Conventional estimators such as OLS are highly sensitive to extreme values, which can distort coefficient estimates and reduce the efficiency of the model. In the context of spatial econometric modeling, particularly GWPR, the influence of such atypical observations may lead to misleading interpretations of local parameter estimates and spatial heterogeneity.

To mitigate this issue, the application of robust estimation methods becomes necessary. One widely recognized approach is the M-estimator, which assigns lower weights to outlying observations during the estimation process. This property allows the model to capture the general production trends across districts while minimizing the distortive impact of extreme cases such as Timor Tengah Selatan and Sumba Barat Daya. By incorporating robust estimation within the GWPR framework, the analysis is able to provide more reliable insights into the spatial determinants of maize production in ENT, ensuring that the results are not disproportionately driven by a small subset of districts.

The bandwidth estimates vary markedly across districts. Flores Timur (968,403.22) and Lembata (884,373.59) have relatively large bandwidths, whereas Timor Tengah Selatan (4,310.65) and Sumba Barat (37,024.60) have much smaller values. Under the adaptive Gaussian weighting scheme, these differences indicate that the effective spatial scale used for local estimation differs by location; they should not be interpreted directly as stronger or weaker spatial dependence.

Table 2. Optimal bandwidth estimation results across districts in East Nusa Tenggara (ENT)

Location	Bandwidth
Sumba Barat	37,024.60
Sumba Timur	191,782.76
Kupang	148,067.74
Timor Tengah Selatan	4,310.65
Timor Tengah Utara	588,955.51
Belu	66,651.22
Alor	553,606.78
Lembata	884,373.59
Flores Timur	968,403.22
Sikka	425,293.74
Ende	230,077.18
Ngada	183,957.12
Manggarai	115,217.68
Rote Ndao	318,431.83
Manggarai Barat	168,195.42
Sumba Tengah	527,318.85
Sumba Barat Daya	141,332.36
Nagekeo	805,067.84
Manggarai Timur	84,961.22
Sabu Raijua	165,413.55
Malaka	259,286.52
Kota Kupang	175,375.85

The results in Table 2 show considerable variation in the estimated bandwidth values across districts in ENT. Flores Timur (968,403.22) and Lembata (884,373.59), for example, have the widest bandwidths, indicating that the model in these areas requires a broader spatial scope to adequately capture regional patterns. In contrast, Timor Tengah Selatan (4,310.65) and Sumba Barat (37,024.60) display much narrower bandwidths, suggesting that spatial dependence in these districts can be explained within a more localized context.

These differences show that the spatial scale governing the local weighting is not uniform across ENT. Large bandwidths produce more gradual distance decay and therefore borrow information from a broader geographical neighborhood,

whereas small bandwidths emphasize observations nearer to the target district. This interpretation concerns the weighting scale of the local estimator and does not, by itself, constitute a test of spatial autocorrelation.

These differences point to the presence of spatial heterogeneity across the region. Districts with larger bandwidths tend to share more similar characteristics with their surrounding areas, while those with smaller bandwidths are more strongly shaped by localized influences. This variation underscores an important feature of the spatial model: the optimal scale of analysis is not uniform across ENT but must be determined specifically for each location.

After determining the optimal bandwidth for each location, the analysis proceeds to estimate the parameters of the GWPR model using the M-estimator, which is designed to provide robust results in the presence of outliers. The outcomes of the global regression parameter estimation are summarized in Table 3.

Table 3. Estimated global parameters of the geographically weighted panel regression (GWPR) model with the M-estimator

Parameter	Coefficient	*p*-Value
Intercept	0.0050	0.82
X_1 (maize harvested area)	1.0090	<0.05
X_2 (agricultural extension workers)	0.0213	0.38
X_3 (farming households)	0.2070	<0.05
X_4 (annual rainfall)	0.1010	<0.05
X_5 (mean annual temperature)	0.0008	<0.05

The results of the global parameter estimation using the M-estimator are presented in Table 3. The intercept coefficient (0.0050) is statistically insignificant ($p = 0.82$). Harvested area (X_1; $\beta = 1.0090$, $p < 0.05$), farming households (X_3; $\beta = 0.2070$, $p < 0.05$), annual rainfall (X_4; $\beta = 0.1010$, $p < 0.05$), and mean annual temperature (X_5; $\beta = 0.0008$, $p < 0.05$) show statistically significant positive associations with maize production in the reported global specification. Agricultural extension workers (X_2; $\beta = 0.0213$, $p = 0.38$) are not statistically significant at the 5% level. These coefficients describe conditional statistical associations and should not be interpreted as causal effects. The non-significant extension coefficient likewise does not demonstrate that extension services are ineffective, because measurement, timing, omitted variables, and local heterogeneity may influence the estimated relationship.

Conversely, the number of agricultural extension workers (X_2) has a *p*-value of 0.38. The lack of statistical significance for agricultural extension workers indicates that extension services may not serve as a primary determinant of maize output when compared to land and climatic factors.

Overall, these results underscore the dominant influence of land resources and climatic conditions in determining maize production in ENT, while the contribution of extension-related variables appears relatively marginal at the global level. This provides a strong rationale for employing local modeling approaches such as GWPR to better capture spatial heterogeneity and location-specific dynamics [7].

While the global model provides a broad overview of the relationship between explanatory variables and maize production, it relies on the assumption that these relationships are uniform across all districts. In reality, agricultural production is strongly shaped by spatial heterogeneity, particularly due to variations in land resources, climatic conditions, and socio-economic characteristics. To capture these local differences more accurately, the analysis proceeds with a GWPR. A summary of Local Coefficient Estimates of Maize Production Using GWPR in ENT is presented in Table 4.

Table 4. Summary of local coefficient estimates of maize production using geographically weighted panel regression (GWPR) in East Nusa Tenggara (ENT)

Parameter	Min	Max	Mean	Variance
β_0 (Intercept)	0.007	1.560	0.068	0.112
β_1 (Harvested area, X_1)	–1.130	1.069	0.839	0.244
β_2 (Agricultural extension workers, X_2)	–0.046	0.630	0.049	0.018
β_3 (Farming households, X_3)	–1.660	0.090	–0.086	0.012
β_4 (Annual rainfall, X_4)	–0.140	1.649	0.090	0.120
β_5 (Mean annual temperature, X_5)	–4.435	0.120	–0.210	0.890

Table 4 summarizes the local coefficient estimates of maize production using GWPR in ENT. The results show considerable cross-district variation in magnitude and sign. Harvested area (β_1) ranges from −1.130 to 1.069 with a mean of 0.839; agricultural extension workers (β_2) range from −0.046 to 0.630 with a mean of 0.049; farming households (β_3) range from −1.660 to 0.090 with a mean of −0.086; rainfall (β_4) ranges from −0.140 to 1.649 with a mean of 0.090; and temperature (β_5) ranges from −4.435 to 0.120 with a mean of −0.210. Negative local coefficients are not interpreted as causal evidence that increasing an input necessarily reduces production. They may reflect local agronomic conditions, omitted factors, collinearity, measurement differences, or the effective local sample structure. The sign changes therefore reinforce the need for cautious, location-specific interpretation.

The intercept (β_0) is positive on average but varies widely, suggesting that baseline productivity differs among districts. Such differences may arise from variations in infrastructure, access to agricultural inputs, or adoption of technology. Harvested area (β_1) emerges as the most influential factor, with a high mean coefficient of 0.839. This aligns with Mondiana et al. [10], who emphasized the role of land availability in determining crop output. Yet, negative coefficients in certain districts remind us that expanding farmland does not always guarantee higher yields, particularly where soil fertility, irrigation, or farming practices are suboptimal.

The effect of agricultural extension workers (β_2) is relatively modest, with a small average coefficient (0.049). This suggests that extension services may provide localized benefits but have not consistently translated into significant productivity gains. Similarly, the number of farming households (β_3) shows a negative mean effect (–0.086), indicating that larger farmer populations may not improve production when land is fragmented, or resources are inefficiently managed.

Climatic factors play an especially important role. Rainfall (β_4) is generally supportive of production, with mostly positive coefficients, though excessive rainfall in some districts reduces yields. Temperature (β_5), on the other hand, shows the strongest negative impact, with a wide range and an overall

negative mean (–0.210), underlining maize's vulnerability to heat stress. These findings are consistent with Etwire et al. [42], who observed similar sensitivities in other tropical regions.

From a food-security perspective, these results suggest potential rather than prescriptive implications. The observed spatial variation can help identify districts in which land, climate, or institutional relationships merit closer agronomic investigation. However, the model does not include fertilizer use, irrigation availability, soil characteristics, market accessibility, or technology adoption, and it has not been validated through agricultural-expert elicitation or policy-scenario analysis. Consequently, the findings should inform subsequent assessment rather than be treated as direct policy guidance.

Based on the summary of local coefficients in Table 4, it is evident that the effects of explanatory variables on maize production vary considerably across districts. This variation highlights the presence of spatial heterogeneity, indicating that factors found to be significant in one location may not exert the same influence elsewhere. Consequently, the use of a local model becomes essential to capture these spatially varying relationships more accurately.

Subsequently, the local model enables the identification of variables that significantly influence maize production in each district. This analysis provides a more nuanced understanding of the determinants of production in relation to the specific characteristics of each area. The complete results are presented in Table 5.

Table 5. Significant variables of maize production identified by geographically weighted panel regression (GWPR) across districts in East Nusa Tenggara (ENT)

Location	Significant Variable(s)	Local Coefficient	*p*-Value
Sumba Barat	X_4; X_5	1.649; −4.435	0.023; 0.032
Sumba Timur	X_1	0.958	0.011
Kupang	X_1; X_5	1.069; 0.093	0.007; 0.024
Timor Tengah Selatan	X_1; X_3; X_5	0.000; 0.000; 0.000	0.004; 0.021; 0.010
Timor Tengah Utara	X_1; X_5	0.992; 0.006	0.016; 0.027
Belu	X_1	0.981	0.029
Alor	X_1; X_4	1.016; 0.020	0.013; 0.032
Lembata	X_1	1.008	0.020
Flores Timur	X_1	1.007	0.027
Sikka	X_1	0.996	0.009
Ende	X_1	0.978	0.023
Ngada	X_1; X_2; X_5	0.973; 0.032; 0.016	0.007; 0.026; 0.018
Manggarai	X_1	0.898	0.031
Rote Ndao	X_1; X_5	1.012; 0.017	0.014; 0.034
Manggarai Barat	X_1	1.033	0.017
Sumba Tengah	X_1; X_5	0.976; −0.003	0.012; 0.024
Sumba Barat Daya	X_1; X_5	1.023; −0.157	0.008; 0.028
Nagekeo	X_1	0.998	0.022
Manggarai Timur	X_1; X_5	0.635; −0.323	0.010; 0.021
Sabu Raijua	X_1	0.950	0.036
Malaka	X_1	1.062	0.015
Kupang City	X_1; X_5	1.040; 0.075	0.009; 0.030

Note: X_1 = maize harvested area; X_2 = agricultural extension workers; X_3 = farming households; X_4 = annual rainfall; X5 = mean annual temperature. Local coefficients and *p*-values are reported to three decimal places; the significant local coefficients for Timor Tengah Selatan are smaller than 0.0005 in absolute value and therefore appear as 0.000 at this precision.

Table 5 presents the location-specific explanatory variables that were statistically significant in the GWPR model across districts in ENT. The results indicate substantial spatial variation in the significance and magnitude of the local relationships between the explanatory variables and maize production. Among the five explanatory variables, harvested area (X_1) was the most consistently significant determinant, with statistically significant effects in 21 of the 22 districts. Sumba Barat was the only district in which X_1 was not statistically significant. With the exception of Timor Tengah Selatan, where the local coefficient was smaller than 0.0005 in absolute value (displayed as 0.000), the significant local coefficients of X_1 were consistently positive and ranged from 0.635 in Manggarai Timur to 1.069 in Kupang. This pattern indicates that greater harvested area is generally associated with higher maize production across most districts and highlights the important role of cultivated land availability in determining agricultural production, consistent with previous studies identifying cultivated area as an important determinant of crop production in resource-constrained regions [43].

Rainfall (X_4) showed a more localized influence, being statistically significant only in Sumba Barat and Alor, with positive local coefficients of 1.649 and 0.020, respectively. This result suggests that the contribution of rainfall to maize production is geographically concentrated rather than uniform across ENT. Mean annual temperature (X_5), in contrast, was significant in 10 districts, namely Sumba Barat, Kupang, Timor Tengah Selatan, Timor Tengah Utara, Ngada, Rote Ndao, Sumba Tengah, Sumba Barat Daya, Manggarai Timur, and Kupang City. Its local coefficients varied in direction across districts, with positive effects in several locations and negative effects in Sumba Barat, Sumba Tengah, Sumba Barat Daya, and Manggarai Timur. These contrasting local effects indicate that the relationship between temperature and maize production is spatially differentiated and may depend on local agroclimatic conditions. Rather than implying a uniformly negative temperature effect, the results suggest that climatic influences on maize production are localized and context-dependent.

Human-related factors exhibited substantially more limited spatial significance. Agricultural extension officers (X_2) were significant only in Ngada, with a positive local coefficient of

0.032. The number of farming households (X_3) was significant only in Timor Tengah Selatan according to the local *p*-value output. These geographically restricted effects suggest that human and institutional factors may influence maize production only under particular local conditions. This interpretation is broadly consistent with evidence from Sub-Saharan Africa indicating that extension services and farmer-related factors can play more context-specific roles compared with land and climatic determinants [44].

Overall, the spatial variation in significant variables emphasizes the necessity of adopting location-specific agricultural strategies rather than uniform regional policies. In particular, strengthening land use efficiency, improving climate adaptation strategies, and tailoring extension programs to local contexts are critical for enhancing maize production. From a broader perspective, these results provide empirical support for the argument that sustainable food security in ENT depends not only on expanding cultivated area but also on integrating climate resilience into agricultural planning.

The next step is to evaluate the stability of the estimators in the GWPR model when employing the M-estimator, using a series of controlled simulations under varying levels of data contamination. The results of bias and MSE under each outlier scenario are presented in Table 6.

Table 6. Bias and Mean Squared Error (MSE) of the geographically weighted panel regression (GWPR) model with M-estimation under different outlier percentages

Outlier Percentage	Bias	MSE
10%	2.36	3.28
15%	2.62	4.48
20%	3.66	5.52

Table 6 reports the aggregate Bias and MSE of the robust GWPR estimator under the three contamination proportions. Relative to the simulation reference parameters, Bias increases from 2.36 at 10% contamination to 2.62 at 15% and 3.66 at 20%, while MSE increases from 3.28 to 4.48 and 5.52, respectively. The monotonic increase indicates that estimation accuracy deteriorates as the contaminated fraction grows.

Within the examined 10%–20% scenarios, the deterioration is gradual rather than abrupt, which is consistent with estimator stability under the stated simulation design. However, this conclusion is conditional on the exact contamination-generation mechanism and reference parameters used in the simulation; these settings are those described in Section 3. The experiment does not establish predictive superiority over standard GWPR, conventional panel regression, or alternative spatial models because those estimators were not benchmarked under an identical validation design. Alternative robust local estimators, such as geographically weighted quantile regression, have also been proposed for handling outliers in spatially heterogeneous data [45] and would be a natural comparator in such a benchmark.

5. CONCLUSIONS

This study applied robust fixed-effects GWPR with M-estimation to maize production across 22 districts in ENT during 2020–2023. The analysis focuses on district-level maize-production associations rather than on a multidimensional food-security outcome. Local coefficients show substantial cross-district variation; harvested area has the largest positive mean local coefficient (0.839), while climatic and socio-institutional covariates vary in magnitude and sign across locations.

The findings demonstrate that maize production in ENT cannot be adequately explained using spatially homogeneous assumptions. Instead, production dynamics are shaped by complex interactions between land resources, climatic conditions, and local agricultural characteristics. The local parameter estimates generated by GWPR provide evidence that factors influencing maize production in one district may not exert the same influence in another, emphasizing the importance of geographically differentiated analysis in agricultural research.

From a methodological perspective, the study adapts established M-estimation to a fixed-effect GWPR workflow and evaluates its stability through contamination simulations. Bias increases from 2.36 at 10% contamination to 3.66 at 20%, while MSE increases from 3.28 to 5.52. These results support a bounded claim of estimator stability within the reported scenarios; they do not establish superiority over standard GWPR or alternative spatial models without a common predictive benchmark.

Several limitations should be acknowledged. The analysis contains only four annual observations per district (2020–2023), which limits inference about long-term trends. The explanatory set excludes fertilizer use, irrigation availability, soil characteristics, market accessibility, and technology adoption. The simulation conclusions are conditional on the contamination mechanism, randomization strategy, and implementation settings described in Section 3. The global Moran's I diagnostics (Table 1) did not indicate significant residual spatial autocorrelation in any year, although this result is conditional on the Queen contiguity weights used and on the exclusion of four island districts without contiguous neighbors. Future work should extend the temporal coverage, enrich the covariate set, and compare conventional panel regression, standard GWPR, robust GWPR, and alternative spatial econometric models using a common predictive design. Scalable GWR implementations developed for very large datasets [46] and recent scoping reviews of GWR methods and applications [47] offer methodological guidance for such extensions.

Overall, the study provides a focused application of robust spatio-temporal modeling to geographically varying determinants of maize production. Its contribution lies in combining fixed-effects GWPR, robust M-estimation, and contamination-based simulation at district level. Policy relevance should be interpreted as supporting geographically differentiated agricultural assessment rather than as direct evidence of food-security outcomes or causal policy effects.

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