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Improving Sugarcane Production Prediction: Robust Estimation of Geographically Weighted Panel Regression

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Abstract: Accurate prediction of sugarcane production is vital for effective agricultural planning in Indonesia. However, traditional methods can be hampered by spatial variations and outliers in yield data. This study addresses this challenge by employing Geographically Weighted Panel Regression (GWPR) with a robust M-estimator to predict sugarcane production in East Java, Indonesia, from 2019 to 2022. Addressing the challenges posed by outliers in sugarcane yield data from regions like East Java. This research combines panel data analysis and geospatial regression to capture the intricate spatial and temporal dynamics of sugarcane production. Based on MAE the results demonstrate the significant improvement in predictive performance achieved through robust estimation within the GWPR model, emphasizing the effectiveness of this approach in refining sugarcane production forecasts in the Indonesian context. This study highlights the potential of robust estimation methods to enhance agricultural forecasting models in Indonesia's sugarcane industry.

Keywords: sugarcane production prediction; outlier; Robust estimation; M estimation; Geographically Weighted Panel Regression.

1 Introduction

Indonesia is the 9th largest sugarcane producer among the world in 2023 after Brazil, India, China, Unites States, Thailand, Mexico, Paskistan and Argentina. The data from Food and Agriculture Organization of the United Nations (FAO), shows that Indonesia's total sugarcane production in 2023 reached 28.9 million tons. Even though Indonesia is among the top ten world sugarcane producers, there are still challenges in meeting its domestic sugar needs [1]. Indonesia, a key player in the global sugarcane industry, grapples with challenges in balancing sugarcane production, consumption, and import dynamics. The nation's significant sugar import dependence reflects the complexities of meeting domestic demand among fluctuating production levels and consumption patterns [2]. Comparison of sugar cane production, sugar production, sugar demand and sugar imports in Indonesia in 2023 is presented in table 1.

Table 1: Sugarcane Production, Sugar Production, Sugar Needs, and Sugar Imports in Indonesia (2023) (Million tons)

Aspect	Quantity
Sugarcane Production	28.9
Sugar Production	2.77
Sugar Needs*	6.2
Sugar Deficit	3.43
Sugar Imports**	4.3
Surplus imports	0.87

* Sugar needs are calculated based on per capita sugar consumption (23 kg/year) and population growth projections

** Sugar imports include refined sugar and raw crystal sugar

Based on the data above, Indonesia still experienced a sugar deficit of 3.43 million tons in 2023. To meet this shortage, Indonesia must import sugar from other countries. In 2023, Indonesia imported 4.3 million tons of sugar. Indonesia faces a challenge in meeting its domestic sugar demand. While the country produces sugarcane, the raw material for sugar, it still relies heavily on imports to fulfill its needs [3].

The largest sugarcane producer in Indonesia is East Java. According to data from the Central Statistics Agency (BPS) in 2023, East Java produced **1.12 million tons of sugarcane**, equivalent **to 49.63%** of total national sugarcane production [4]. Predicting sugarcane productivity in East Java based on its influencing factors is one strategy to reduce reliance on sugar imports. The research about factors that influencing sugarcane production was conducted by [5]. Sugarcane production is influenced by various factors, two of the most significant of which are **climate** and **cane planting area**. By considering

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spatial variations in production, the study aims to provide localized insights for optimizing sugarcane production. One approach to modeling the variability between location is Geographically Weighted Panel Regression (GWPR). GWPR is a method utilized to analyze panel data and capture diverse relationships. It is a combination of panel regression and geographically weighted regression (GWR).

1.1 Research Problem

Several studies have explored the effectiveness of Geographically Weighted Panel Regression (GWPR) for analyzing economic and environmental data [6] pioneered its use in a fixed effects panel model to study Beijing's economic development. This method proved superior to traditional cross-sectional GWR and panel data models in terms of accuracy and precision. Subsequent research by [7] and [8] further solidified this finding. Cai applied GWPR to analyze the impact of climate variations on corn production in the US, while Danlin investigated the effects of high-speed rail use in China. Both studies, like Yu's (2010), demonstrated the advantages of GWPR compared to cross-sectional GWR.

An approach utilized to calculate parameters within the GWPR involves the application of weighted least squares, a method discussed by [9] and [10], although this method is sensitive to outliers, as noted by [11]. Outliers can arise due to various factors, such as data collection errors, data entry mistakes, or the presence of rare or extreme events. When these outliers are not properly handled, they can distort the calculated parameter values, leading to misleading conclusions and potentially hindering decision-making processes. Outliers in the data can mislead the least squares method used in regression models. This leads to biased parameter estimates, meaning the calculated values may not accurately reflect the true relationships between variables. When outliers are present, the least squares method used in regression models becomes inefficient. This means the estimated parameters may not be reliable because the method struggles to account for the extreme data points, leading to large residual values (the difference between predicted and actual values) [12].

To address this challenge, robust parameter estimation methods have been developed. These methods are designed to be less sensitive to outliers, ensuring that the estimated parameters accurately reflect the underlying relationships between variables in the data. Robust parameter estimation methods, on the other hand, are able to withstand the influence of outliers, providing more reliable and accurate parameter estimates [13]. This is particularly important in fields like economics, sociology, and environmental science, where outliers can have a significant impact on the interpretation of data and the formulation of policies.

1.2 Objective of the paper

The objective is to improve the accuracy of sugarcane production prediction by incorporating spatial and temporal variations using a Geographically Weighted Panel Regression (GWPR). Several robust parameter estimation methods are available, each with its own strengths and limitations. Some of the most commonly used methods include **M-estimators.** These methods assign weights to data points based on their distance from the model's fitted values, with outliers receiving lower weights to minimize their impact. This approach has been employed in studies by [14] and [15]. [14] utilized a robust geographically weighted method to identify multivariate spatial outliers and mitigate their influence on regression coefficient estimates in both simulated data and freshwater chemistry data for Great Britain. [15] study applied a robust estimation method utilizing local absolute deviation (LAD) to calculate GWR parameters for simulated data. Their findings indicated that LAD did not provide a dependable variance estimate with a straightforward calculation for the estimated coefficients due to the iterative nature of coefficient estimation procedures. [16] employed the M estimator within the Geographically and Temporally Weighted Regression (GTWR) framework to analyze outlier-inclusive data. Their study demonstrated that employing robust GTWR modeling resulted in a superior model compared to traditional GTWR approaches. Based on [17] suggests that among various methods, the M estimator is the most straightforward and efficient approach. Sugarcane yield predictions help the government determine whether Indonesia can meet domestic sugar needs or requires imports. Yield predictions allow the government to allocate appropriate subsidies, such as for fertilizers or agricultural machinery. Accurate yield predictions guide decisions on the timing of sugar imports or exports. Yield predictions affect policies on the purchasing price of sugarcane by sugar mills, directly impacting sugarcane farmers' livelihoods. With stable income for farmers, local economies in sugarcane-producing regions can grow more robustly.

1.3 Research Methodology

This research examines sugarcane production data from East Java, the main raw material utilized in sugar production. The dataset was gathered from the Indonesia Statistic Central Agency over a four-year period (2019 – 2022) and the Statistical Of National Leading Estate Crops Commodity (2019-2022). In this research, the study incorporated six independent variables (X), such as the area of sugarcane plantations(X1), rainfall patterns (X2), rainy days occurrences (X3), sunlight duration (X4), temperature levels(X5), and humidity levels(X6). In contrast, the dependent variable (Y) focused solely on sugarcane production in East Java.

The data analysis procedures were conducted in the following steps:

1. Describing the data with heatmap and performing Breusch-Pagan (BP) test to detect spatial heterogeneity. The hypotheses is as follow

$H_0: \sigma^2_{(u_1,v_1)} = \sigma^2_{(u_2,v_2)} = \cdots = \sigma^2_{(u_n,v_n)} = \sigma^2$ (there is no spatial heterogeneity)

H_1: *at least one i where* $\sigma_i^2 \neq \sigma^2; i = 1,2, \ldots, n$ (there is spatial heterogeneity)

The BP test statistic is as follow:

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

Where

h : vector element

$$h_i = \left(\frac{e_i^2}{\sigma^2} - 1\right)$$

Z : explanatory variables matrix

H_0 is accepted if $BP \leq \chi^2_{(p+1)}$, while $\chi^2_{(p+1)}$ is the critical value of chi-square distribution and p is the number of explanatory variables.

2. Performing outlier detection using Z-scores. An outlier is identified when the Z-score exceeds +3 or falls below -3.
3. Calculating Euclid Distance (d_{ij}) between the location to – *i* and location to – *j* with the following formula

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

4. Determining bandwidth using CV optimum criteria

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

5. Calculating weighting matrix (w_{ij}) with adaptive gaussian kernel as the following formula:

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

6. Performing Fixed Effect Geographically Weighted Panel Regression with M Estimation with the following algorithm
   a. Estimate $\hat{\beta}^0$ and get $\varepsilon_i^{(0)}$
   b. Calculate $\hat{\sigma}_i = 1.4826\ MAD$,
   where
   $$MAD = \frac{median|x_i - median(x_i)|}{0.6745}$$
   c. Calculate $u_i = \frac{e_i}{\hat{\sigma}_i}$
   d. Determine the objective function and calculate the weighting value
   $$w_i^*(u_i)^{(0)} = \frac{\psi(u_i)^{(0)}}{u_i^{(0)}}$$
   e. Calculate $\hat{\beta}_M$ using the Weighted Least Square (WLS) method with weighted w_i
   $$\widehat{\beta_M} = (X^T W^m X)^{-1} X^T W^m y$$
   f. Set residual in step (e) as residual step (a)
   g. Iterating reweighted least square (IRLS) on new weighting until $\hat{\beta}^M$ convergent

2. Materials and Methods

The descriptive of the average data of sugarcane production 2019-2022 among districts/city within East Java with heatmap is illustrated in Figure 1.

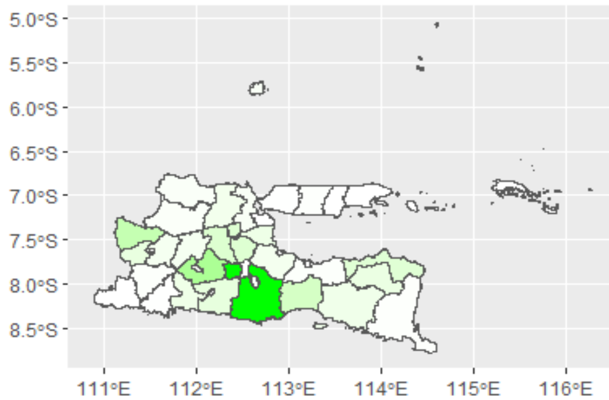

Fig. 1: Sugarcane yield production heatmap in east Java 2019-2022

Figure 1 illustrates that areas with darker shades indicate higher levels of sugar production in those regions. Malang Regency emerged as the leading sugarcane producer in East Java during the 2019-2021 period. Conversely, Figure 1 reveals that four districts – Pacitan, Pamekasan, Blitar, and Surabaya – entirely lacked sugarcane production throughout this timeframe.

The next procedures is testing spatial heterogeneity with BP test. The results of spatial heterogeneity testing are shown in Table 2.

Table 2: Breusch- Pagan test Result

BP	P-value	Decision
4,378	0.0034	Reject H_0

The result of BP test show that there is spatial heterogeneity in sugarcane productivity between each area ($P<0.05$). Then the data can be analyzed using spatial analysis, one of which is geographically weighted panel regression

The next step is finding an outlier with Z score. Based on the detection of outliers in GWPR data, there were outliers in eight East Java districts. These districts included Malang in 2019 – 2022, Blitar in 2020, Ngawi in 2021 and Tuban in 2022. Since our Geographically Weighted Panel Regression (GWPR) model deals with potential outliers in the data, a robust estimator was necessary. This research employed the M-estimator to achieve a reliable model.

Geographically Weighted Panel Regression Using M estimation

The results of the global parameter estimation for the Geographically Weighted Panel Regression (GWPR) model using M-estimation are presented in Table 3

Table 3: Global Parameter Estimation for GWPR model with M estimation

Variable	Coefficients	T value	P value
Area of sugarcane plantations(X1)	20.0170	11.859	0.0045
Rainfall patterns (X2)	-1,1471	0.4254	0.0948
Rainy Days occurrences (X3)	6.1267	9.6501	0.0075
Sunlight Duration (X4)	26.596	3.9770	0.0095
Temperature Levels(X5)	24.890	5.4759	0.0080
Humidity Levels(X6)	0.0004	0.0354	0.8345

The results demonstrated that the area of sugarcane plantations (X1), rainy days occurrences, sunlight duration and temperature levels have a significant effect on sugarcane production while the rainfall patterns and humidity levels have no effect on sugarcane yield (Table 3). The area of sugarcane plantations, rainy days occurrences, sunlight duration, and temperature levels have been identified as significant factors affecting sugarcane production, while rainfall patterns and humidity levels do not have a substantial impact on sugarcane yield. Research by [18] highlights the ecological adaptability of sugarcane in different climate zones in China, emphasizing the importance of natural climate characteristics on sugarcane production. Additionally, studies by [19] and [20] discuss the influence of temperature, water availability, and weather variations on sugarcane yield, supporting the claim that these factors play a crucial role in sugarcane production. Furthermore, the research by [21] and [22] delve into the impact of climate change on sugarcane production, emphasizing the sensitivity of sugarcane to temperature changes and solar radiation. These studies provide insights into how climate variability can affect sugarcane yields. Additionally, the work by [23] and [24] further support the relationship between incident sunlight, temperature, and sugarcane yield, indicating the importance of these factors in determining crop productivity. In contrast, studies such as those by [25] and [26] suggest that factors like precipitation and humidity may not have a direct impact on sugarcane yield, aligning with the notion that rainfall patterns and humidity levels do not significantly affect sugarcane production.

The study entitled The Effect of Rainfall and Rainy Days on Sugarcane Production (Saccharum Officinarum Linn) at the Kwala Bingai Plantation of PT. Perkebunan Nusantara II [27] concluded that rainfall did not affect sugarcane production. This is in line with the research of [28], which concluded that rainfall did not affect sugarcane yields. However, according to [29] rainfall has an important effect on sugarcane growth, sugarcane ripening, pest and disease attacks related to air humidity, and sugar productivity related to the smoothness and accuracy of harvesting and transportation operations. This is emphasized by the opinion of [30] that sugarcane plants need a lot of water during the plant growth period or vegetative period which plays a role in increasing the weight of the sugarcane stem which includes the diameter of the stem and the height of the stem.

The results of the local parameter estimation model with the M-estimator, specific to each district/city in East Java, are summarized in Table 4.

Table 4: Summary of Local Parameter Estimate for GWPR model with M estimation

Parameter	Min	Max	Mean	Standard deviation
β_1	-2867,69	1,28	-1717,78	707,12
β_2	0,78	5,46	4,49	1,79
β_3	-11,38	0,59	-2,22	2,79
β_4	-0,006	0,12	0,12	0,35
β_5	-34,80	570,62	57,14	153,66
β_6	-0,02	0,07	0,03	0,01

Table 4 summarizes the local parameter estimates derived using the M-Estimator for each district/city in East Java. The results reveal interesting spatial variations. The area of sugarcane plantations exhibited the highest standard deviation, indicating significant sugarcane plantations differences across the observed regions. Conversely, the humidity level had the smallest standard deviation, suggesting a relatively consistent fertilizer usage pattern across the study area. The estimated parameters for rainfall patterns ranged from 0.78 to 5.46, while sunlight duration varied from -0.006 to 0.12 in their parameter estimates.

The significant variables at each location are presented in Table 5

Table 5: Significant variabel at each location

Number	District/city	Significant variable
1	Pacitan District	X1, X2
2	Ponorogo District	X1,X2
3	Trenggalek District	X1,X2
4	Tulungagung District	X1,X2,X3,X6
5	Blitar District	X2
6	Kediri District	X1,X3
7	Malang District	X1
8	Lumajang District	X1
9	Jember District	X1,X2
10	Banyuwangi District	-
11	Bondowoso District	X1,X2,X4,X5
12	Situbondo District	X1
13	Probolinggo District	X1
14	Pasuruan District	X1,X3
15	Sidoarjo District	X1,X2
16	Mojokerto District	X1
17	Jombang District	X1,X5
18	Nganjuk District	X1
19	Madiun District	X1
20	Magetan District	X1
21	Ngawi District	X1
22	Bojonegoro District	X1

23	Tuban District	X1
24	Lamongan District	X1
25	Gresik District	X1,X2,X5,X6
26	Bangkalan District	X1
27	Sampang District	X1
28	Pamekasan District	X1
29	Sumenep District	X1
30	Kediri City	X1
31	Blitar City	X1,X2,X3,X4
32	Malang City	X1,X2
33	Probolinggo City	-
34	Pasuruan City	-
35	Mojokerto City	X2
36	Madiun City	X1
37	Surabaya City	X1
38	Batu City	X2

The variable area of sugarcane plantation is significant in 84.2% of areas in East Java, specifically in 32 districts/cities. The variable rainfall is significant in 12 areas in East Java, including Pacitan district, Ponorogo district, Trengglaek district, Tulungagung district, Blitar district, Jember district, Bondowoso district, Sidoarjo District, Gresik district, Blitar city, Mojokerto city and Batu city. Rainy days occurrence is significant in 4 areas, namely Tulungagung district, Kediri district, Pasuruan district, and Blitar city. Sunlight duration is significant in only 2 locations, Bondowoso district, and Blitar city. Temperature levels are significant in 3 locations, Bondowoso district, Jombang district, and Blitar city. Humidity levels are significant in 2 locations, Gresik district, and Malang city.

The extent of land allocated to sugar cane cultivation significantly influences sugar cane production. Studies have indicated that changes in land use to traditional productive systems for sugar cane can have positive effects on development [32]. For instance, cultivating sugar cane on a large land area, such as nearly 1 million hectares, can lead to substantial gross yields, emphasizing the importance of land area in sugar cane production [33]. Climatic variables also play a significant role in influencing sugar production. Studies have shown that factors such as temperature, photosynthetically active radiation (PAR), water availability, and other climatic elements have a direct impact on sugar accumulation traits in crops like sugarcane [34]. Weather variability and climate change have been identified as crucial factors affecting sugarcane production [35]. The relationship between climatic variability and water footprint on sugarcane production has been studied, emphasizing the influence of elements like rainfall, temperature, humidity, sunshine, and wind speed [36]. Various climatic factors such as sunlight, temperature, humidity, and windstorm have been identified as significant determinants affecting sugarcane production [37]. the critical influence of climatic variables on sugar production, highlighting the need for comprehensive strategies to mitigate the impact of changing climates on crop yields.

3. Results and Conclusion

Assessing the Performance of GWPR models with M Estimation

The performance of the GWPR model with M estimator can be seen from the R^2. R^2 is a statistical measure representing the proportion of predictable variance in the dependent variable from the independent variable(s) in a regression model. In this study, the GWPR model yielded an R-squared value of 0.88. This means that 88% of the variance in sugarcane production can be explained by six variables: area of sugarcane plantation, rainfall patterns, rainy days occurrences, sunlight duration, temperature levels, and humidity level. This value is considered better compared to the R^2 value of 0.78 from the GWPR model. To assess the predictive accuracy of a model, various evaluation metrics suitable for the model type and problem context can be used. Common metrics like Mean Absolute Error (MAE) indicate the average absolute differences between model predictions and actual values. A lower MAE signifies higher prediction accuracy [38]. The MAE for the GWPR model with M estimation is 39.28, while the MAE for the GWPR model is 69.77. This indicates that the GWPR model with M estimation is better than the GWPR model. This is consistent with research by [39] which concludes that the GTWR model with robust estimators is better than the GTWR model in handling outlier data.

The sugarcane yield data from 2019 to 2022 in East Java exhibited outliers in various regions such as Malang, Blitar, and Ngawi districts. Due to the presence of outliers, a robust approach utilizing the M estimator was employed. Findings indicated that plantation areas had a significant impact on production across all locations. With an R-squared value of 0.88, the GWPR model with M estimation is better than standar GWPR. MAE of GWPR M estimation demonstrated strong predictive capabilities for sugarcane production**.**

Conflicts of Interest Statement

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