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COMPARISON OF WEIGHT MATRIX IN HOTSPOT MODELING IN WEST KALIMANTAN USING THE GSTAR METHOD

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Abstract. *This research aims to investigate the usefulness of the Generalized Space-Time Autoregressive (GSTAR) approach in predicting the number of fire hotspots in West Kalimantan Province. Specifically, the study compares the performance of the Queen contiguity method and the uniform weight matrix. Fires in the forests and on the land in West Kalimantan are severe problems that cause harm to the environment and other adverse effects. Data on fire hotspots were collected from four different regencies in West Kalimantan between January 2018 and March 2023 to provide the information used in this study. Compared to the uniform weight matrix, the study results reveal that the Queen contiguity weight matrix produces more accurate results. This is evidenced by the fact that the Root Mean Squared Error (RMSE) and Mean Absolute Deviation (MAD) values are lower in the Queen contiguity weight matrix. Based on these findings, more effective techniques for preventing forest and land fires are anticipated to be considered for planning purposes.*

Keywords: GSTAR, Uniform Weight Matrix, Queen Contiguity

1. Introduction

In Indonesia, forest and land fire disasters occur annually. This is because there is a growing demand for communal land use for agricultural purposes and the establishment of towns. The change of land, primarily into oil palm plantations, is the root cause of forest and land fires, particularly on peatlands [1].

West Kalimantan is a region that frequently sees fires in the peatlands and forests regularly. This is because West Kalimantan Province, situated on the island of Kalimantan, is distinct from the islands of Sumatra and Papua in terms of the sorts of peatlands it exhibits. Peatland is most of this province's territory, in an area

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traversed by the equator. The ability to hold biomass, litter, and mineral soil are all qualities common to peatland environments. Peatlands are also characterized by their high flammability [2]

Forest and land fires are natural disasters that often occur in Indonesia. This occurrence is common in West Kalimantan, one of the regions we are discussing. These fires have several detrimental effects on life, including the destruction of ecosystems, a reduction in biodiversity, a loss in the economic worth of forests and land productivity, climate change, and the appearance of smoke pollution [3].

Indicators of forest and land fires can be identified through hotspots. According to the data analysis, four districts have the largest average number of hotspots. These districts are the Ketapang District, the Sanggau District, the Sintang District, and the Landak District—in that order. As a result, modelling and estimating the number of hotspots is of utmost significance for planning mitigation and response measures.

In spatial analysis, selecting the spatial weight matrix is a crucial step that can influence the modelling results. The Queen Contiguity and the uniform weight matrix, respectively, are two methods that are frequently utilized. All neighbours are given the same weight in a uniform weight matrix, which does not consider distance or other spatial relationships. The Queen Contiguity matrix, on the other hand, takes into account neighbours that share edges or corners with the unit of analysis. As a result, it offers a more comprehensive depiction of spatial interconnections [4].

In modelling spatial-temporal data, the Generalized Space-Time Autoregressive (GSTAR) method is frequently utilized due to its capacity to capture the complexity and dynamism of data dispersed throughout space and time. By utilizing the GSTAR approach, the number of hotspots can be anticipated with greater precision, which in turn contributes to developing more efficient mitigation strategies [5].

Researchers Mukhayar et al. used the GSTAR approach to conduct research to forecast the number of cases of dengue fever in several different sites in West Kalimantan [6]. Using the GSTAR-Krigging model, Abdullah et al. also researched to predict rainfall at sites in West Java that had not been observed previously [7]. The GSTAR approach was utilized by Huda et al. in order to model the increase in Gross Domestic Product in five different countries. According to the MSE score, the uniform weight matrix generates the most accurate model [8].

A comparison of the effectiveness of two different kinds of weight matrices in modeling the number of hotspots is carried out using the Generalised Space-Time Autoregressive (GSTAR) approach. The evaluation is carried out to determine which of the two approaches is the most effective: the Queen Contiguity weight matrix compared to the uniform weight matrix. This evaluation is carried out to measure the performance of the two ways.

This research aims to assess the performance of two different types of weight matrices, uniform weight and Queen Contiguity, in modelling the number of hotspots in West Kalimantan Province using the GSTAR technique. By carrying out this comparison, a more optimal approach can be developed for modelling and predicting the distribution of hotspots. This would allow the information obtained to be more valuable in the efforts being made to prevent and manage forest and land fires in the region.

2. Theoretical Basis

The AR model was the basis for the development of the STAR model, which was followed by the GSTAR model, which is a development of its predecessor. This research restricted uses the Generalized Space-Time Autoregressive (GSTAR) method of an order [1;1], which uses a uniform weight matrix and a queen contiguity weight matrix.

2.1. *AR Model*

The AR model can be structured in the following general form [9].

$$Y_t = \Phi_1 Y_{t-1} + \cdots + \Phi_p Y_{t-p} + e_t, \tag{2.1}$$

where:

$$\begin{aligned} Y_t &: \text{ observation at time } t, \\ Y_{t-p} &: \text{ observation at time } t-p, \\ \phi_p &: \text{ AR parameter of order } p, \\ e_t &: \text{ error at time } t. \end{aligned}$$

2.2. *STAR Model*

In the STAR model, a parameter matrix is utilized, and all parameters are assumed to be identical. In its most basic form, the STAR model can be described as follows [10].

$$Y_t = \left(\sum_{k=1}^{p} \sum_{t=0}^{\lambda_k} \phi_{kl} W^{(l)} Y_{t-k} \right) + e_t \tag{2.2}$$

where:

$$\begin{aligned} \lambda_s &: \text{ spatial lag}, \\ Y_t &: (N \times 1) \text{ of observation vector at time } t, \\ Y_{t-k} &: (N \times 1) \text{ of observation vector at time } t-k, \\ \Phi_{kl} &: \text{ STAR parameters}, \\ W^{(l)} &: \text{ weight matrix in spatial lag } k, \\ e_t &: \text{ the white noise with mean vector0 and variance-covariance matrix } \sigma^2 I. \end{aligned}$$

2.3. *GSTAR Model*

GSTAR model with autoregressive order p and spatial order $\lambda_1, \lambda_2, \cdots, \lambda_k$, GSTAR $(p\lambda_1, \lambda_2, \cdots, \lambda_k)$ can be written as follows general form [11].

$$\mathbf{Y_t} = \left(\sum_{k=1}^{p} \sum_{l=0}^{\lambda_k} \Phi_{kl} W^{(l)} \mathbf{Y_{t-k}} \right) + \mathbf{e_t} \tag{2.3}$$

where:

$$\begin{aligned}
Y_t &: (N \times 1) \text{ of observation vector at time } t,\\
\lambda_k &: \text{ spatial order of the } k^{th} \text{ autoregressive term},\\
\Phi_{kl} &: \text{ the diagonal matrices with the diagonal elements as autoregressive,}\\
&\quad \text{and the space time for each location } (\Phi_{kl}^{(1)}, \cdots, \Phi_{kl}^{(N)}),\\
W^{(l)} &: \text{ weight matrix in spatial lag } k,\\
e_t &: \text{ the white noise with mean vector } \mathbf{0} \text{ and variance-covariance matrix } \sigma^2 I.
\end{aligned}$$

The GSTAR model with first-order spatial lag and first-order autoregressive or GSTAR [1;1] has the following general formula [12]:

$$Y_t = \Phi_{10} Y_{t-1} + \Phi_{11} W_{(*)} Y_{t-1} + e_t, \tag{2.4}$$

where,

$$Y_t = \begin{bmatrix} Y_t^{(1)} \\ Y_t^{(2)} \\ \vdots \\ Y_t^{(n)} \end{bmatrix}; \Phi_{10} = \begin{bmatrix} \Phi_{10}^{(1)} & 0 & \cdots & 0 \\ 0 & \Phi_{10}^{(2)} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \Phi_{10}^{(2)} \end{bmatrix}; \Phi_{11} = \begin{bmatrix} \Phi_{11}^{(1)} & 0 & \cdots & 0 \\ 0 & \Phi_{11}^{(2)} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \Phi_{11}^{(2)} \end{bmatrix}; e_t = \begin{bmatrix} e_t^{(1)} \\ e_t^{(2)} \\ \vdots \\ e_t^{(n)} \end{bmatrix}.$$

Matrix $W_{(*)}$ is a weight matrix, and ϕ is a diagonal matrix where each entry on the diagonal is a parameter. Equation (2.6) can also be written as follows.

$$Y_t = (\Phi_{10} + \Phi_{11} W_{(*)}) Y_{t-1} + e_t. \tag{2.5}$$

2.4. *Selection of Weight Matrix in GSTAR Model*

The weight matrix is a characteristic of the GSTAR space-time model that can be used to identify the model. This matrix describes the relationships that exist between different geographical areas. In a general sense, the weight matrix can be expressed in the following form [13]:

$$\mathbf{W} = \begin{bmatrix} 0 & w_{12} & \cdots & w_{1j} \\ w_{12} & 0 & \cdots & w_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ w_{i1} & w_{i2} & \cdots & w_{ij} \end{bmatrix}.$$

2.4.1. *Uniform Weight Matrix*

This weight matrix gives the same value for each site, which is why it is frequently utilized for data containing similar places or consistent distances between locations [14].

$$w_{ij} = \frac{1}{m}, \tag{2.6}$$

$$W = \begin{bmatrix} 0 & \frac{1}{m} & \cdots & \frac{1}{m} \\ \frac{1}{m} & 0 & \cdots & \frac{1}{m} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{m} & \frac{1}{m} & \cdots & 0 \end{bmatrix},$$

where $m = n - 1$, n is the number of locations and w_{ij}=0 if $i = j$.

2.4.2. *Queen Contiguity Weight Matrix*

The weight of this location is derived from regions near one another or whose corner points meet; hence, these areas are assigned the value $w_{ij} = 1$, while the value $w_{ij} = 0$ is assigned to other areas. First, the matrix needs to be normalized so that the sum of each row in the matrix equals one [15].

$$w_{ij} = \frac{c_{ij}}{c_i}, \tag{2.7}$$

where:

$$\begin{aligned} c_{ij} &: i \text{ is the row element}, j \text{ is the column}, \\ c_i &: \text{ total elements of the } i - \text{row} \\ i, j &: 1, 2, \cdots, n, \\ n &: \text{ number of locations.} \end{aligned}$$

2.5. *Parameter Estimation*

The GSTAR model can be written as a linear model, and the Ordinary Least Square (OLS) method can be utilized to estimate the autoregressive parameters of the model [16]. Because the GSTAR model is a regression model, the Ordinary Least Squares (OLS) approach is typically utilized to estimate the parameters that are associated with this model. The following linear equation can be constructed using the GSTAR [1;1] formula:

$$Y = X\beta + e. \tag{2.8}$$

This equation can then be modified with different locations so that for the i^{th} location, it can be formulated in the following equation.

$$Y_i = X_i\beta_i + e_i, \tag{2.9}$$

where Y_i is the observation for the i^{th} location ($i = 1, 2, \cdots, N$), and $\beta_i = (\phi_{10}^{(1)}, \phi_{11}^{(1)})$. If for $V_i(t) = \Sigma_{j \neq i} W_{ij} Y_j(t)$, then equation (2.9) can be translated into the following matrix.

$$\begin{bmatrix} Y_i(1) \\ Y_i(2) \\ \vdots \\ Y_i(T) \end{bmatrix} = \begin{bmatrix} Y_i(1) & V_i(0) \\ Y_i(0) & V_i(1) \\ \vdots & \vdots \\ Y_i(T-1) & V_i(T-1) \end{bmatrix} \begin{bmatrix} \phi_{10}^{(1)} \\ \phi_{11}^{(1)} \end{bmatrix} + \begin{bmatrix} e_i(1) \\ e_i(2) \\ \vdots \\ e_i(n) \end{bmatrix}.$$

By virtue of the fact that $\beta_i = \left(\phi_{10}^{(1)}\right)$ is, in fact, an autoregressive parameter for both time and space, the vector of estimation that is obtained through the use of the OLS method can be expressed as follows [17]:

$$\hat{\beta} = \left[X'X\right]^{-1} X'Y. \tag{2.10}$$

2.6. *Model Accuracy Level*

Accuracy measurements enable us to evaluate how well a model accomplishes its intended purpose, such as accurately forecasting values or properly classifying data. By measuring its accuracy, we can establish whether a model is enough or needs further development.

In situations where more than one model is being investigated, accuracy metrics are utilized to evaluate and contrast the performance of the models. Generally speaking, the model with the best accuracy rate is the best. The following are some examples of the several sorts of model accuracy measures that are typically utilized [18].

(1) **Root Mean Square Error (RMSE)**

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(X_i - Y_i)^2},$$

where:

$$\begin{aligned} m &: \text{ number of observations,} \\ X_i &: i^{th} \text{ actual data,} \\ Y_i &: i^{th} \text{ estimation data.} \end{aligned}$$

(2) **Mean Absolute Percentage Error (MAPE)**

$$MAPE = \frac{1}{m}\sum_{i=1}^{m}\left|\frac{Y_i - X_i}{Y_i}\right|,$$

where:

$$\begin{aligned} m &: \text{ number of observations,} \\ X_i &: i^{th} \text{ actual data,} \\ Y_i &: i^{th} \text{ estimation data.} \end{aligned}$$

(3) **Mean Absolute Deviation**

$$MAD = \frac{1}{m}\sum_{i=1}^{m}|X_i - Y_i|,$$

$$\begin{aligned} m &: \text{ number of observations,} \\ X_i &: i^{th} \text{ actual data,} \\ Y_i &: i^{th} \text{ estimation data.} \end{aligned}$$

3. Discussion

3.1. *Descriptive Analysis*

The research conducted was quantitative, and the data collected was numerical. More specifically, the data collected was information regarding the number of fire points. One may observe the progression of this research by referring to the flow diagram presented in Figure 1 below.

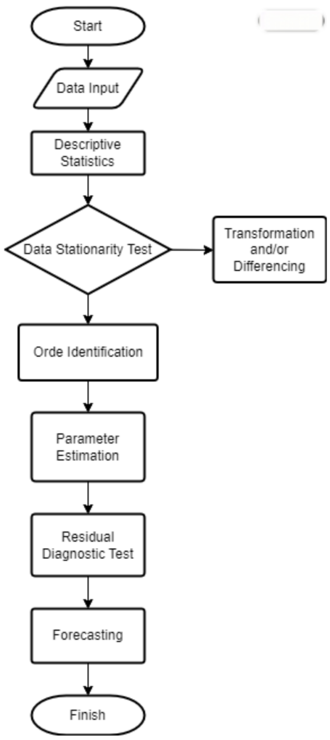


Figure. 1: The Flowchart

The map that may be found in Figure 2 depicts the distribution of hotspots across the several districts that make up West Kalimantan Province. The degree of fluctuation in the frequency of fires is depicted on this map through the use of colour coding, which provides a clear visualisation of the spatial distribution of fires that occur.

Based on Figure 2, it is evident that there are six regions or cities that are highlighted in yellow, and the average number of hotspots in these regions is less than 5,304. There are four regions or cities that have an average number of fire hotspots measuring between 5,304 and 8,000, and these areas are highlighted in orange. On the red map, there are an average of more than 8,000 hotspots, which

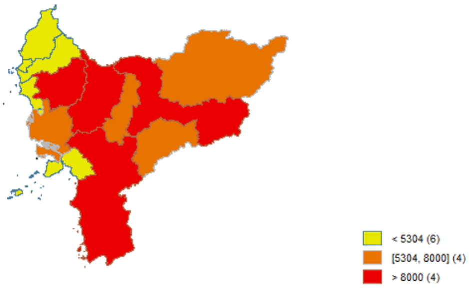


Figure. 2: Hotspot Distribution Map

are comprised of four districts or cities.

Secondary data were obtained from the website *https://sipongi.menlhk.go.id/* before being used in this investigation. An average of more than 8,000 hotspots may be found in West Kalimantan, which includes Ketapang Regency, Landak Regency, Sanggau Regency, and Sintang Regency ($n = 4$). This research makes use of data on the distribution of hotspots in West Kalimantan, which constitutes the high category. The hotspot distribution data that was utilized is data from the period beginning in January 2018 and ending in March 2023 ($T = 75$). In the course of this investigation, four different variables were utilized, namely:

(1) $Y_t^{(1)}$: Number of hotspots in Landak Regency,
(2) $Y_t^{(2)}$: Number of hotspots in Ketapang Regency,
(3) $Y_t^{(3)}$: Number of hotspots in Sanggau Regency,
(4) $Y_t^{(4)}$: Number of hotspots in Sintang Regency.

The descriptive statistics of the data that were utilised in the GSTAR modelling are presented in Table 1. It is important to note that the displayed data contain the minimum, maximum, average, and standard deviation values for each district that was examined.

Table 1: Descriptive Statistics on the Number of Hotspot

Regency/City	Total Observations	Minimum	Maximum	Mean	Standard Deviation
Ketapang	75	0	6208	358	1075
Landak	75	0	2402	109	356
Sanggau	75	0	5305	225	808
Sintang	75	0	2903	130	410

Based on Table 1, the total number of monthly data observations in this study was 75 for each district, and it is well known that the distribution of hotspots that occurred in the four districts of West Kalimantan Province varied substantially. This is something that is currently recognised. A value of zero hotspot cases is the bare minimum for each of the four districts. With 6,208 cases, Ketapang Regency had the highest maximum value, while Landak Regency had the lowest maximum value, with only 2,402 cases available. Ketapang Regency in Indonesia has the highest standard deviation value, while Landak Regency has the lowest number.

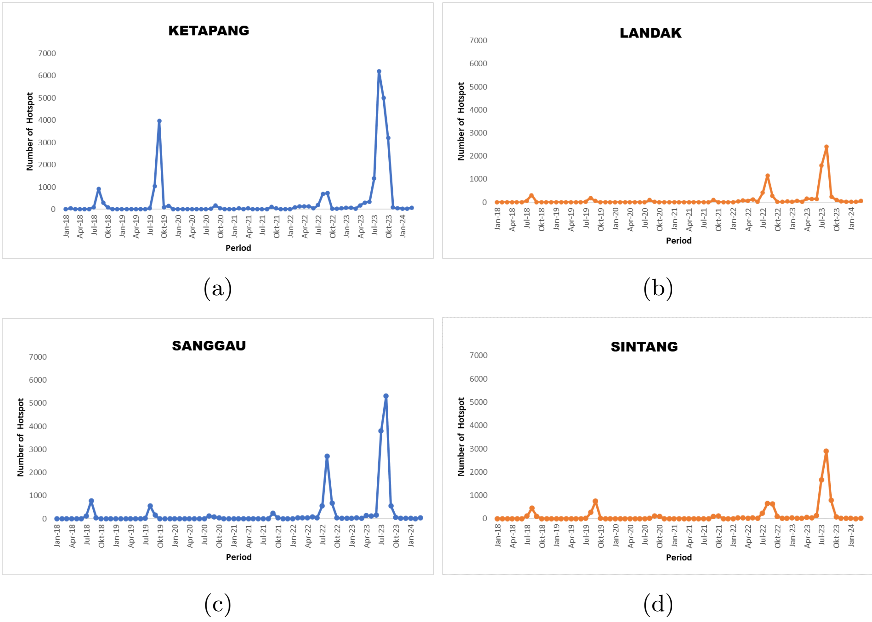


Figure. 3: Time Series Data Plot Number of Hotspot

Based on Figure 3, for the purpose of gaining a better understanding of the rise and fall in the total data on the distribution of hotspots over time, a time series graphic was created for each site like this.

3.2. *Data Stationarity*

The stationarity of the data is the most important requirement that must be satisfied in order to conduct our time series analysis. Both the mean and the variance of the data that is used must be stationary. If the data are not stationary in terms of their mean and variance, then it is necessary to do processes including data transformation and differencing.

3.2.1. *Stationarity in Variance*

Based on figure 3, due to the fact that the data does not exhibit a steady variance, it is necessary to transform the data. Considering that the data in question has a value of zero, the square root transformation should be utilized. The formula that is used to perform the square root transformation is as follows.

$$Z_t = \sqrt{Y_t}, \tag{3.1}$$

where Z_t is the transformed data and Y_t is the observation data for $t = 1, 2, \cdots, T$.

3.2.2. *Stationarity Within the Mean*

The Augmented Dickey-Fuller Test, also known as the ADF test, is a method that can be utilised to determine whether or not the data is stationary within the average. You can view the results of the ADF tests conducted in the Ketapang, Landak, Sanggau, and Sintang Regencies in Table 2.

Table 2: Test ADF Data

Regency/City	P-value	Decision	Information
Ketapang	0.04	H_0 rejected	Stationary
Landak	0.03	H_0 rejected	Stationary
Sanggau	0.02	H_0 rejected	Stationary
Sintang	0.01	H_0 rejected	Stationary

Based on Table 2, every district possesses a p-value for the hotspot data that is less than 0.05, which indicates that all of the data is stationary in the mean. In order to proceed to the next level of the analysis of the data.

3.3. *Calculation of Weight Matrix in GSTAR Model*

Calculating the weight matrix that will be used is the next stage. The GSTAR model's weight matrix describes the interaction between the various sites. Both the queen contiguity weight matrix and the uniform weight matrix are utilised in this study. Both of these weight matrices are distinct from one another. Through the utilisation of Equation (2.6), the uniform weight matrix is computed. Considering that there are four different places, the value of m in this equation is three. At the same time, a queen contiguity weight matrix is produced using information about the neighbourhood. These districts are assigned a value of 1 in this matrix, while districts that do not have any direct borders are assigned a value of 0. This matrix is used to categorise districts. The value 0 is used to fill the diagonal of the matrix, then the matrix needs to be normalized used equation (2.7). The matrix that is generated is structured as follows.

$$W_{(U)} = \begin{bmatrix} 0 & 0.33 & 0.33 & 0.33 \\ 0.33 & 0 & 0.33 & 0.33 \\ 0.33 & 0.33 & 0 & 0.33 \\ 0.33 & 0.33 & 0.33 & 0 \end{bmatrix}, \text{ and } W_{(Q)} = \begin{bmatrix} 0 & 0 & 0.5 & 0.5 \\ 0 & 0 & 1 & 0 \\ 0.33 & 0.33 & 0 & 0.33 \\ 1 & 0 & 0 & 0 \end{bmatrix},$$

where:

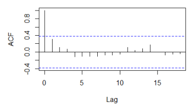
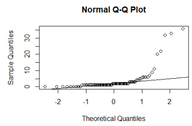
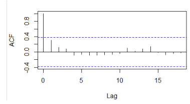
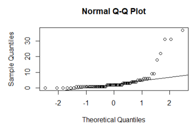
$W_{(U)}$: uniform weight matrix,

$W_{(Q)}$: queen contiguity weight matrix.

3.4. *Parameter Estimation*

Table 3 presents the parameter estimates that were derived from the GSTAR model that was utilised for the analysis of hotspot data in four districts located within the province of West Kalimantan.

Table 3: Parameter Estimation Results and Residual Diagnostics

Weight	Parameter				Independence	Normality	Information
Uniform	$\phi_{10}^{(1)}$	0,197	$\phi_{11}^{(1)}$	1,103			White Noise
	$\phi_{10}^{(2)}$	1.219	$\phi_{11}^{(2)}$	-0.353			
	$\phi_{10}^{(3)}$	0.883	$\phi_{11}^{(3)}$	-0.207			
	$\phi_{10}^{(4)}$	0.209	$\phi_{11}^{(4)}$	0.447			
Queen Contiguity	$\phi_{10}^{(1)}$	0.195	$\phi_{11}^{(1)}$	1.016			White Noise
	$\phi_{10}^{(2)}$	2.025	$\phi_{11}^{(2)}$	-0.894			
	$\phi_{10}^{(3)}$	0.883	$\phi_{11}^{(3)}$	-0.207			
	$\phi_{10}^{(4)}$	1.113	$\phi_{11}^{(4)}$	-0.223			

Based on Table 3, as a result of the fact that it is known that the models derived from both matrices satisfy the white noise assumption, it is possible to utilise the two models to make predictions regarding the number of fire hotspots in the regions of Landak Regency, Ketapang Regency, Sanggau Regency, and Sintang Regency.

3.5. *Selection of the Best Model*

One of the most crucial things to do while conducting a modelling analysis of the number of hotspots in West Kalimantan Province using the GSTAR approach is to select which model is the most appropriate to employ. When picking the optimal model, it is necessary to conduct many assessments of statistical criteria. These evaluations are designed to guarantee that the chosen model has the highest level of accuracy in forecasting the number of hotspots. The outcomes of picking the most suitable model on the basis of these criteria are represented in Table 4. The statistical values that were obtained are then utilised to determine which model is the most appropriate. This table offers information about the models that were tested, along with the statistical values that were obtained.

Table 4: Model Accuracy Value

Weight	RMSE	MAPE	MAD
Uniform	4.795	**27.88**	2.418
Queen Contiguity	**4.406**	27.91	**2.275**

Based on Table 4, the GSTAR model, which makes use of the queen contiguity weight matrix and has RMSE and MAD values that are lower than those of the uniform weight matrix, is the most effective. Based on the queen contiguity weight matrix, the GSTAR [1;1] equation model can be expressed as follows.

$$\begin{bmatrix} Y_t^{(1)} \\ Y_t^{(2)} \\ Y_t^{(3)} \\ Y_t^{(4)} \end{bmatrix} = \left(\begin{bmatrix} 0.195 & 0 & 0 & 0 \\ 0 & 2.025 & 0 & 0 \\ 0 & 0 & 0.883 & 0 \\ 0 & 0 & 0 & 1.113 \end{bmatrix} + \begin{bmatrix} 1.016 & 0 & 0 & 0 \\ 0 & -0,894 & 0 & 0 \\ 0 & 0 & -0.207 & 0 \\ 0 & 0 & 0 & -0.223 \end{bmatrix} \begin{bmatrix} 0 & 0 & 0.5 & 0.5 \\ 0 & 0 & 1 & 0 \\ 0.33 & 0.33 & 0 & 0.33 \\ 1 & 0 & 0 & 0 \end{bmatrix} \right) \begin{bmatrix} Y_{t-1}^{(1)} \\ Y_{t-1}^{(2)} \\ Y_{t-1}^{(3)} \\ Y_{t-1}^{(4)} \end{bmatrix}$$

$$\begin{aligned} \text{Landak} &: Y_t^{(1)} = 0.195Y_{t-1}^{(1)} + 0.508Y_{t-1}^{(3)} + 0.508Y_{t-1}^{(4)}, \\ \text{Ketapang} &: Y_t^{(2)} = 2.025Y_{t-1}^{(2)} - 0.894Y_{t-1}^{(3)}, \\ \text{Sanggau} &: Y_t^{(3)} = -0.069Y_{t-1}^{(1)} - 0.069Y_{t-1}^{(2)} + 0.883Y_{t-1}^{(3)} - 0.069Y_{t-1}^{(4)}, \\ \text{Sintang} &: Y_t^{(4)} = -0.223Y_{t-1}^{(1)} + 1.113Y_{t-1}^{(4)}. \end{aligned}$$

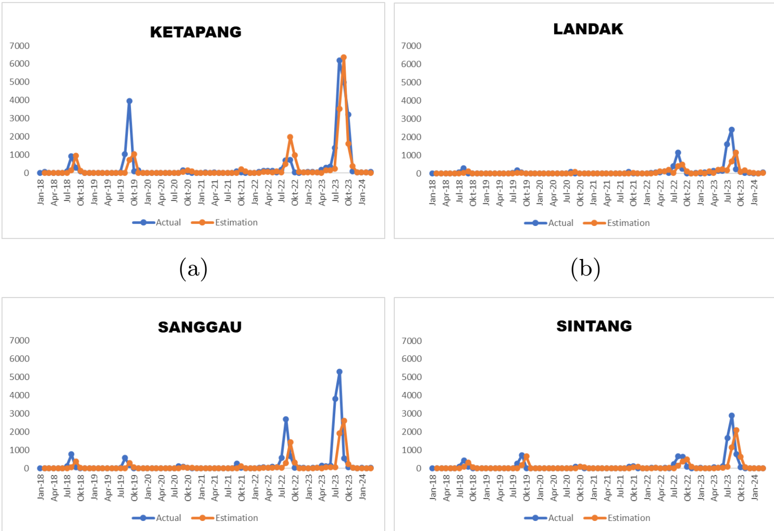
3.6. *Contrasting the Actual Values with the Estimated Values*

As shown in Figure 4, a comparison plot is displayed between the actual data and the estimated data that was derived from the results of the GSTAR modelling for the number of hotspots in the several districts that make up West Kalimantan Province. The purpose of this plot is to determine how accurate the model is in forecasting the number of hotspots. By contrasting the actual data with the estimated data, we are able to determine the degree to which the GSTAR model is able to recreate the actual data patterns.

Figure 4 illustrates regardless of whether or not the model is effective. There is a high degree of congruence or overlap between the actual data and the anticipated data lines, which is an indication that the model predictions are extremely accurate. In addition, this graphic assists in determining whether or not the model is properly capturing trend patterns in the historical data regarding the amount of hotspots being used. The fact that the GSTAR model is able to follow the pattern of changes in the number of hotspots over time is demonstrated by the fact that the real data trends and the estimated data trends are consistent with one another. By comparing these two data sets, it is possible to determine the areas in which the model may need to be more accurate. For example, the presence of outliers or substantial variations that were not predicted properly by the model can be seen as examples of inaccuracies in the model. The presence of significant discrepancies between the real data and the estimated data may be an indication that the model requires some modifications or enhancements.

4. Conclusion

As a result of the findings of the investigation that has been carried out, it is possible to conclude that the Queen Contiguity weight matrix is superior to the uniform weight matrix when it comes to modeling the distribution of hotspots in the regions of Landak, Ketapang, Sanggau, and Sintang. The lower values of Root



(a) (b) (c) (d)

Figure. 4: Comparison Plot of Actual and Estimated Data

Mean Squared Error (RMSE) and Mean Absolute Deviation (MAD) prove this. According to the findings of the study, the distribution of hotspots in the Regencies of Ketapang, Landak, Sanggau, and Sintang is not only influenced by previous events that occurred in their place but it is also influenced by previous events that occurred in a variety of other locations. For instance, according to the developed model, the number of hotspots in Ketapang Regency is affected by previous events within Ketapang Regency itself, with a coefficient of 0.195. Additionally, Sanggau and Sintang Regency, each of which had a value of 0.508, also had an impact on the number of hotspots in Ketapang Regency—applying the Queen Contiguity weight matrix results in more precise forecasts when modeling the number of fire hotspots in West Kalimantan Province.

As a result, these findings can serve as a reference for developing more efficient forest and land fire mitigation plans. This research would assist the government, and other relevant parties make more informed decisions about managing forest fire catastrophes. Therefore, selecting the appropriate weight matrix is of utmost significance in spatial-temporal analysis to acquire a more accurate and trustworthy model. To conduct additional studies, the GSTAR model can be compared to other weight matrices, such as the Rook contiguity weight matrix, inverse distance, and others.

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