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ANALYSIS OF FOREST FIRE CASES USING GSTAR(1;1) MODEL WITH SPATIAL ROOK CONTIGUITY WEIGHTS MATRIX IN WEST KALIMANTAN

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Abstract. *In West Kalimantan, forest and land fires cause damage to ecosystems, the loss of biodiversity, and detrimental repercussions on both health and the local economy. Extreme weather and land clearance for agricultural and plantation purposes are the primary reasons. This study aims to investigate forest fires' spatial and temporal patterns by employing the Generalized Space-Time Autoregressive (GSTAR)(1;1) approach with spatial rook contiguity weights. From January 2020 to March 2024, the data used consisted of the number of monthly forest fires that occurred in the Ketapang, Sanggau, Sintang, Landak, and Sekadau Regencies. According to the findings, the spatial pattern demonstrates strong interactions between regions in which flames in one area affect fires in other locations. The temporal pattern demonstrates that prior fires can impact fires that occur in the subsequent period, depending on the area. The model has an average MAPE value of 13%, indicating that this model has a fairly good level of accuracy and can be used for making predictions. This study concludes that a better understanding of the spatial-temporal patterns of forest fires can enhance early warning systems and enable rapid responses to potential future fires.*

Keywords: Forest fires, gstar, spatial temporal analysis

1. Introduction

One of the most significant environmental issues in Indonesia, particularly in the province of West Kalimantan, is the occurrence of forest and land fires. These fires not only cause harm to ecosystems and lead to the loss of biodiversity, but they also significantly influence public health and the economics of the surrounding area [1]. Additionally, forest fires contribute to air pollution, which frequently extends to neighboring nations, as well as emissions of greenhouse gases, which increase the

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effects of climate change worldwide [2]. Several factors cause forest fires in West Kalimantan, the most significant of which are the clearance of land for agricultural and plantation purposes, the occurrence of extreme weather conditions, such as extended dry seasons, and the use of land management practices that are not sustainable [3]. A lack of efficient law enforcement and supervision is another factor that contributes to the worsening of forest fire cases. Local communities frequently experience various health issues as a consequence of forest fires, including respiratory issues and other ailments brought on by exposure to smoke [4].

A comprehensive understanding of the spatial and temporal patterns of forest and land fire events is of utmost importance when developing successful fire prevention and suppression tactics. An acceptable method for analyzing the dynamics of the number of forest fire instances is the Generalized Space-Time Autoregressive (GSTAR) method, which is applicable in this situation. An array of methodologies and applications that are pertinent to space-time analysis have been established as a result of previous research on GSTAR. The GSTAR model was developed with the express purpose of taking into account the spatial and temporal dependencies that exist between observations. These dependencies are critical in the geographical data gathering and environmental condition monitoring processes.

Multiple research conducted in the past have investigated GSTAR from a variety of perspectives. For discrete data, GSTAR modelling offers a profound understanding of how the model is implemented in that particular setting [5]. Outlier identification in GSTAR was highlighted in a subsequent study, which established that the model is capable of resolving anomalies in the data that was observed [6]. An examination of the usefulness of various spatial weights in defining dependencies between areas or places in a spatial-temporal dataset is presented in the following section, which is a comparison of the weight matrices for the GSTAR (1;1) model [7]. The significance of the model in simulating public health conditions by taking into consideration outlier characteristics is demonstrated by research that has been conducted on the concrete application of GSTAR(1;1) in instances of dengue disease [8]. In the process of developing models for more accurate analysis, one of the most notable efforts that stands out is the modification of the weight matrix in order to improve the performance of GSTAR(1;1) [9]. The new weight matrix that was developed, which makes use of kernel functions, offers a novel approach to the improvement of the representation of spatial relationships in models [10]. A deeper understanding of the dynamic nature of complicated space-time data can be attained through research that investigates stationarity processes with spatial weights and kernel functions. The overall purpose of this research is to shed light on a variety of approaches and innovations that have been implemented in the development of GSTAR in order to overcome the difficulties associated with space-time data analysis through the utilization of a more complete and precise methodology [11].

In situations where data points are not independent of one another, such as in the collecting of geographic data or the monitoring of environmental conditions, the GSTAR model takes into explicit consideration the geographical dependencies that exist between observations. This is especially important in situations when the data points are used. This particular GSTAR model includes lag factors for both spatial and temporal components. The temporal lag implies that an event in a given region affected by events that occurred in previous periods, while the spatial lag indicates that an event influenced by events occurring in adjacent regions. According to the conclusions of the research discussed earlier, several studies demonstrate that the weight matrix is the primary focus of this research. The weight matrix is the GSTAR model component responsible for describing the spatial dependencies between various locations or regions in a spatio-temporal dataset. This component is responsible for explaining the spatial dependencies and their implications. A different name for this particular matrix is the spatial weight matrix, also called the $\mathbf{W}$ matrix. This matrix helps establish the relationship between observations made in one area and those made in areas adjacent to one another [12].

The purpose of this study is to construct a GSTAR(1;1) model with spatial rook contiguity weights by making use of the data that is collected from the number of forest fire cases that occur each month in Ketapang, Sanggau, Sintang, Landak, and Sekadau Regencies over the period spanning from January 2020 to March 2024. The model used in this study is GSTAR(1;1), where the temporal order is $p = 1$ and the spatial order is $\lambda = 1$. This means that the model considers the influence of one previous time period as well as the spatial influence of adjacent regions. The selection of the rook contiguity spatial weight matrix is based on the consideration that this approach represents spatial relationships according to directly shared boundaries between regions. The data will be used to construct the model. As a result of this research, it is hoped that a thorough understanding of the spatial and temporal patterns of forest fires will be presented in the province of West Kalimantan. In addition to assisting in the formation of more effective policies and techniques for preventing and controlling forest fires, the goal of this research is to acquire a better knowledge of the spatial and temporal patterns of forest fire events using this model. This understanding will be used to help formulate more effective policies and strategies. Another purpose of this research is to have a better understanding of the dynamics that are involved in forest fires. The purpose of this initiative is to improve early warning systems and make it easier to respond more quickly to potential forest fires in the future.

2. Theoretical Foundation

2.1. *Generalized Space Time Autoregressive (GSTAR) Model*

Borovkova, Lopuha, and Ruchjana were the ones who initially presented the GSTAR model to the world in 2002. The following is an example of how the GSTAR model might be stated [13]:

$$\mathbf{Y}_t = \left(\sum_{k=1}^{p} \sum_{l=0}^{\lambda_k} \Phi_{kl}^{i} \mathbf{W}^l \mathbf{Y}_{t-k} \right) + \alpha_t, \tag{2.1}$$

where:

$$\Phi_{kl}^{i}=\begin{bmatrix}\Phi_{kl}^{1} & 0 & \cdots & 0\\ 0 & \Phi_{kl}^{2} & \cdots & 0\\ \vdots & \vdots & \ddots & \vdots\\ 0 & 0 & \cdots & \Phi_{kl}^{n}\end{bmatrix}.$$

The weight matrix $\mathbf{W}^{l}$ is a weight matrix that has a spatial lag of l. The residual matrix in the GSTAR model is denoted by the expression $\alpha_t=(\alpha_{1,t},\alpha_{2,t},\cdots,\alpha_{n,t})$. For instance, if the GSTAR model has an autoregressive order of one and a spatial order of one, which is denoted by the notation GSTAR(1;1), then Eq. (2.1) can be represented as follows:

$$\mathbf{Y}_t=\Phi_0\mathbf{W}^0\mathbf{Y}_{t-1}+\Phi_1\mathbf{W}^1\mathbf{Y}_{t-1}+\alpha_t. \tag{2.2}$$

Alternatively, Eq. (2.2) can be expressed in the following manner:

$$\begin{bmatrix}Y_{1,t}\\ Y_{2,t}\\ \vdots\\ Y_{N,t}\end{bmatrix}=\begin{bmatrix}\Phi_{10} & 0 & \cdots & 0\\ 0 & \Phi_{20} & \cdots & 0\\ \vdots & \vdots & \ddots & \vdots\\ 0 & 0 & \cdots & \Phi_{N0}\end{bmatrix}\begin{bmatrix}Y_{1,t-1}\\ Y_{2,t-1}\\ \vdots\\ Y_{N,t-1}\end{bmatrix}$$
$$+\begin{bmatrix}\Phi_{11} & 0 & \cdots & 0\\ 0 & \Phi_{21} & \cdots & 0\\ \vdots & \vdots & \ddots & \vdots\\ 0 & 0 & \cdots & \Phi_{2N}\end{bmatrix}\begin{bmatrix}0 & w_{12} & \cdots & w_{1N}\\ w_{21} & 0 & \cdots & w_{2N}\\ \vdots & \vdots & \ddots & \vdots\\ w_{N1} & w_{N2} & \cdots & 0\end{bmatrix}\begin{bmatrix}Y_{1,t-1}\\ Y_{2,t-1}\\ \vdots\\ Y_{N,t-1}\end{bmatrix}+\begin{bmatrix}\alpha_{1,t}\\ \alpha_{2,t}\\ \vdots\\ \alpha_{N,t}\end{bmatrix}$$

where N is the total number of sites utilized and $i=1,2,\cdots,N$.

2.2. *Spatial Weight in GSTAR Model*

Within the GSTAR model, one such spatial weight is the rook contiguity spatial weight. Rook contiguity is a notion that states that a spatial unit or region is regarded to be a neighbor of another region if both regions possess contacting edges. Rook contiguity is a concept that Rook conceptualized. Utilizing the notion of edge intersection on the map, the rook contiguity matrix is a weighted matrix found in [14]. To determine the weighting values, the conditions that must be satisfied are $w_{ii}^{k}=0$ and $\sum_{i\neq j}w_{ii}^{k}=1$, where i is any of the following: $1,2,\cdots,N$. What follows is a definition of the weighting matrix that may be found in [7]:

$$\mathbf{W}=[w_{ij}]=\begin{bmatrix}0 & w_{12} & \cdots & w_{1N}\\ w_{21} & 0 & \cdots & w_{2N}\\ \vdots & \vdots & \ddots & \vdots\\ w_{N1} & w_{N2} & \cdots & 0\end{bmatrix}.$$

2.3. *Parameter Estimation of GSTAR Model*

The least squares approach is one of the techniques utilized in the GSTAR model to estimate the parameter Φ value. For each location $i=1,2,3,\cdots,N$ and time

$t = 0, 1, 2, \cdots, T$, this model incorporates a sequence of observation values denoted by $Z_{i,t}$. Additionally, the time lag k, the spatial lag l, and the weighting w all play a role in determining the values of these observations. Here is a statement that can be made about the GSTAR model [15]:

$$\mathbf{Z}_{i,t} = \left(\sum_{k=1}^{p} \sum_{t=0}^{\lambda_s} \sum_{i=1}^{N} \Phi_{kl}^{i}(k) \mathbf{Z}_{i,t-k} \right) + \alpha_t.$$

By utilizing the equation $V_{i,t} = \sum_{j=1}^{N} w_{ij} Z_{j,t}$ for $i \neq j$, the model for the first location may be derived:

$$\mathbf{Z}_i = \mathbf{Z}_i^* \Phi + \alpha_t.$$

Following is an example of how the GSTAR(1;1) model can be stated in this scenario:

$$\mathbf{Z}_i = \begin{bmatrix} Z_{i,2} \\ Z_{i,3} \\ \vdots \\ Z_{N,T} \end{bmatrix}, \quad \mathbf{Z}_i^* = \begin{bmatrix} Z_{i,1} & V_{i,1} \\ Z_{i,2} & V_{i,2} \\ \vdots & \vdots \\ Z_{N,T-1} & V_{N,T-1} \end{bmatrix}, \quad \Phi = \begin{bmatrix} \Phi_{kl}^{i} \\ \Phi_{kl}^{i} \\ \vdots \\ \Phi_{kl}^{N} \end{bmatrix}, \quad \alpha_i = \begin{bmatrix} \alpha_{i,2} \\ \alpha_{i,3} \\ \vdots \\ \alpha_{N,T} \end{bmatrix}.$$

The spatial lag, denoted by the letter l, does not extend beyond 0 and 1 in this circumstance. When utilizing the least squares method, the following is how the parameters of the GSTAR(1;1) model are estimated:

$$\Phi = \left((\mathbf{Z}^*)'\mathbf{Z}^*\right)^{-1} ((\mathbf{Z}^*)'\mathbf{Z}).$$

2.4. *Measurement of Accuracy Level of GSTAR Model*

Measuring the correctness of a model is accomplished through the utilization of Mean Absolute Percentage Error (MAPE). MAPE is a measurement that determines the average absolute percentage error between the value seen and the value the model estimated. In estimating observational data, a model with a lower MAPE value suggests a lower error rate. According to the mathematical language, this can be represented as follows [16]:

$$\text{MAPE} = \frac{\sum_{t=1}^{m} \left| \frac{Z_t - \hat{Z}_t}{Z_t} \right| \times 100\%}{m},$$

where:

$$\begin{aligned} m &: \text{the total number of observations}, \\ Z_t &: \text{Actual data at time } t, \text{ where } t = 1, 2, \cdots, m, \\ \hat{Z}_t &: \text{Estimated data at time } t, \text{ where } t = 1, 2, \cdots, m. \end{aligned}$$

3. Discussion

3.1. *Descriptive Statistical Analysis*

For this study, secondary data sources accessible through the SiPongi platform, which the Ministry of Environment and Forestry administers, were utilized to collect the necessary information. Ketapang, Sanggau, Sintang, Landak, and Sekadau are the five districts and cities in West Kalimantan Province with the highest average forest fire cases. The evaluated data comprises the number of cases caused by forest fires in these five districts and towns. This information was gathered over the years, beginning in January 2020 and ending in March 2024, making it suitable for in-depth examination due to its complete coverage.

This research uses a variety of visualization and analytic techniques to provide a better understanding of the data and facilitate a more precise depiction of the data concerning the number of forest fire cases in West Kalimantan Province. The average number of forest fire cases is displayed on the map. The usage of data plots also helps in analyzing trends and patterns in the occurrence of forest fires over time. This is accomplished by providing a temporal picture of the incidents that occurred during the period that is being studied. This analysis also contains descriptive statistics, such as the average, maximum, and minimum number of forest fire cases, to summarize numerical data. These statistics are included in this study. In addition to assisting in identifying trends and anomalies that may arise during the study period, these descriptive statistics are beneficial since they provide a more in-depth context on the analyzed data.

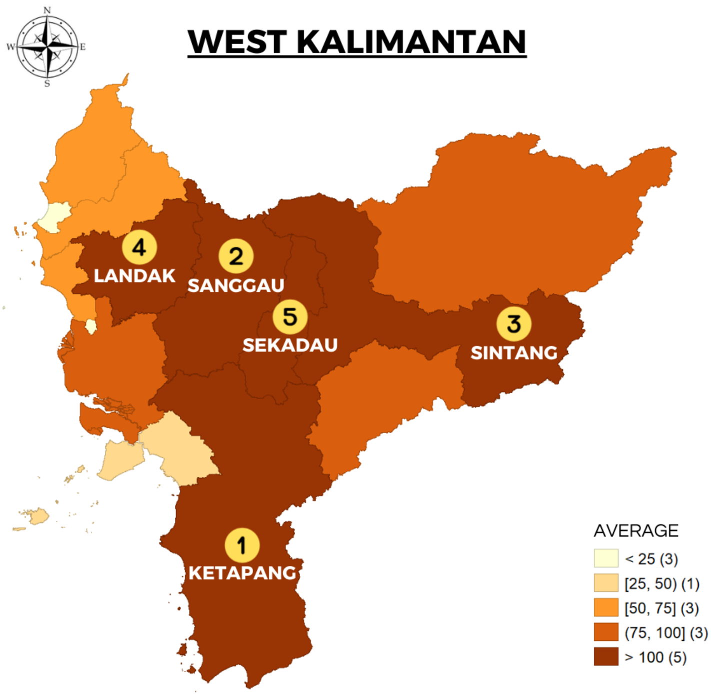
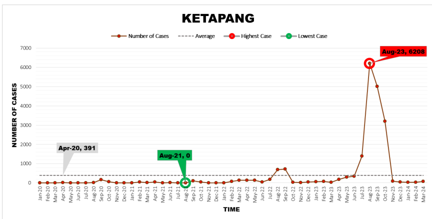
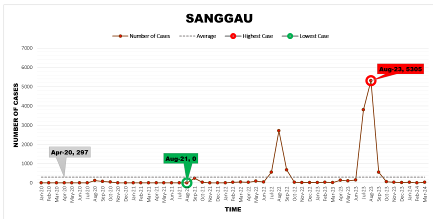


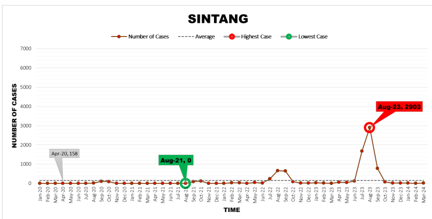
Figure. 1: Map of The Average Distribution of Forest Fire Cases in West Kalimantan per District/City

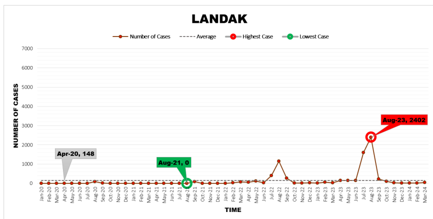
Both Figure 1 and Figure 2 offer graphical representations of the data plots and the outcomes of descriptive statistical analysis for each municipality or district. Not only do these photos display the number of incidents that have occurred in each region, but they also offer visual insights that can assist in comprehending the spread of forest fires and the intensity of those fires in the various regions of West Kalimantan. The purpose of this study is to provide information that is both comprehensive and easy to comprehend regarding the occurrence of forest fires in this province. This will be accomplished using maps, data plots, and descriptive statistics.



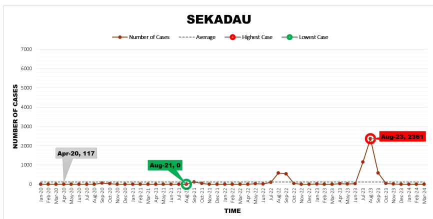


(a) (b)





(c) (d)



(e)

Figure. 2: Data and Plot Descriptive Statistics: (a) Ketapang (b) Sanggau (c) Sintang (d) Landak (e) Sekadau (e) Landak and (d) Sanggau

Based on Figure 1, it can be seen that there is a classification of five regional groups in West Kalimantan Province based on the average number of forest fire cases per Regency/City. These groups are described as follows: Group 1 consists of areas with an average of less than 25 forest fire cases, Group 2 includes areas with an average of between 25 to 50 cases, Group 3 includes areas with an average of between 50 and 75 cases, Group 4 consists of areas with an average of between 75 to 100 cases, and Group 5 includes areas with an average of more than 100 forest fire cases. Figure 1 shows that Ketapang, Sanggau, Sintang, Landak, and Sekadau districts are included in Group 5. This indicates that these five districts have the highest average forest fire cases in West Kalimantan Province. These five districts/cities are located close together geographically, which raises suspicions about a possible spatial link or relationship between these locations regarding forest fire incidents. This geographical proximity indicates the presence of factors contributing to the high number of forest fire cases in these areas. For example, similarities in environmental conditions, agricultural practices, and land use can influence each other.

In Ketapang, there were a total of 391 cases of forest fires, which is shown in Figure 2. This indicates that Ketapang had the highest average number of forest fire cases. On the other hand, Sekadau had the fewest forest fire cases, with only 117 cases registered across the state. In addition, the data demonstrates that Ketapang has the highest number of forest fire cases out of the five districts or cities, with a total of 6208 cases. As can be seen from the data plot, August 2023 was the month in which the five districts and cities saw the highest number of forest fire cases simultaneously. This phenomenon demonstrates a regular temporal pattern in the spread of forest fires in the region, which may indicate that comparable cause variables or supportive environmental circumstances are at play. It was during that time that a fire broke out.

3.2. *Data Stationarity Test*

It is necessary for the data that is utilized in GSTAR modeling to possess stationarity features in both its variance and its mean. As a result, it is essential to analyze to determine whether or not the data remains stationary. Before moving on to the subsequent analysis stage, it is possible to make the data stationary by performing operations such as transformation or differencing if it is not already stationary. To determine whether or not data is stationary, tests such as the Box-Cox and ADF tests can be utilized. The data is not stationary regarding variance, as indicated by the data plot in Figure 2. Therefore, the data must be changed by employing a root transformation, specifically $Z_t = \sqrt{Y_t}$. In order to determine whether or not the data are stationary in the average, the ADF test is carried out after the data have been converted. The results of the ADF tests are presented in the table below. After carrying out the ADF test, it was discovered that the data on the number of forest fire cases in Ketapang Regency was not stationary. On the other hand, Sanggau, Sintang, Landak, and Sekadau Regencies satisfied the expectation of stationarity on average. Therefore, the differencing procedure was first applied to the data of all regencies to make them stationary in the mean. The following are the outcomes of the ADF testing performed before and after the differencing process.

In light of the information presented in Table 1, it is possible to conclude that the data concerning the number of forest fire instances that have been transformed and distinguished are stationary in terms of their variance and their mean. This enables the data to proceed to the subsequent stage of scrutiny.

Table 1: ADF Test Results (p-value)

Location	Before Differencing	After Differencing
Ketapang	0.21310	0.01
Sanggau	0.02070	0.01
Sintang	0.02281	0.01
Landak	0.02532	0.01
Sekadau	0.02348	0.01

3.3. *Calculation of Spatial Weight of GSTAR Model*

Several parameters, including location, are considered when making GSTAR model predictions. For this investigation, spatial weights predicated on rook contiguity are utilized. According to the following expression, the rook contiguity spatial weight matrix can be expressed:

$$\mathbf{W} = \begin{bmatrix} 0 & 0.33 & 0.33 & 0 & 0.33 \\ 0.25 & 0 & 0.25 & 0.25 & 0.25 \\ 0.33 & 0.33 & 0 & 0 & 0.33 \\ 0 & 1 & 0 & 0 & 0 \\ 0.33 & 0.33 & 0.33 & 0 & 0 \end{bmatrix}.$$

3.4. *Parameter Estimation of GSTAR Model*

The estimation of parameters through the use of the least squares method results in the production of multiple significant parameters. Using spatial weights determined by rook contiguity, the following are the outcomes of the parameter estimation process for the GSTAR(1;1) model that was performed.

Table 2: Parameter Estimation

Parameter	Φ_{10}^{1}	Φ_{10}^{2}	Φ_{10}^{3}	Φ_{10}^{4}	Φ_{10}^{5}	Φ_{11}^{1}	Φ_{11}^{2}	Φ_{11}^{3}	Φ_{11}^{4}	Φ_{11}^{5}
Estimation	-0.208	0.812	0.531	-0.372	-0.140	0.905	-1.311	-0.206	0.265	0.326

By Equation (2.2) and Table 2, the GSTAR(1;1) model with spatial rook contiguity weights exhibits the following characteristics:

$$\begin{bmatrix} Z_{1,t} \\ Z_{2,t} \\ Z_{3,t} \\ Z_{4,t} \\ Z_{5,t} \end{bmatrix} = \begin{bmatrix} -0.208 & 0 & 0 & 0 & 0 \\ 0 & 0.812 & 0 & 0 & 0 \\ 0 & 0 & 0.531 & 0 & 0 \\ 0 & 0 & 0 & -0.372 & 0 \\ 0 & 0 & 0 & 0 & -0.140 \end{bmatrix} \begin{bmatrix} Z_{1,t} \\ Z_{2,t} \\ Z_{3,t} \\ Z_{4,t} \\ Z_{5,t} \end{bmatrix}$$

$$+ \begin{bmatrix} 0.905 & 0 & 0 & 0 & 0 \\ 0 & -1.311 & 0 & 0 & 0 \\ 0 & 0 & -0.206 & 0 & 0 \\ 0 & 0 & 0 & 0.265 & 0 \\ 0 & 0 & 0 & 0 & 0.326 \end{bmatrix} \begin{bmatrix} 0 & 0.33 & 0.33 & 0 & 0.33 \\ 0.25 & 0 & 0.25 & 0.25 & 0.25 \\ 0.33 & 0.33 & 0 & 0 & 0.33 \\ 0 & 1 & 0 & 0 & 0 \\ 0.33 & 0.33 & 0.33 & 0 & 0 \end{bmatrix} \begin{bmatrix} Z_{1,t} \\ Z_{2,t} \\ Z_{3,t} \\ Z_{4,t} \\ Z_{5,t} \end{bmatrix}.$$

This is then followed by a description of the model described in the matrix equation that was presented before. This model is based on each site, especially Ketapang, Sanggau, Sintang, Landak, and Sekadau. After that, the GSTAR(1;1) model with spatial rook contiguity weights is expressed in the following manner:

(1) Ketapang.

$$\hat{Z}_{1,t} = -0.208Z_{1,t-1} + 0.299Z_{2,t-1} + 0.299Z_{3,t-1} + 0.299Z_{5,t-1}.$$

The value in Ketapang at time $t-1$ has a coefficient of -0.208, which indicates that it has a negative influence on the value in Ketapang at time t. Furthermore, the value in Ketapang at time t is favourably influenced by the value in Sanggau, Sintang, and Sekadau at time $t-1$, with each of these values having a coefficient of 0.299.

(2) Sanggau.

$$\hat{Z}_{2,t} = -0.328Z_{1,t-1} + 0.812Z_{2,t-1} - 0.328Z_{3,t-1} - 0.328Z_{4,t-1} - 0.328Z_{5,t-1}.$$

The value in Sanggau at time $t-1$ has a coefficient of 0.812, which indicates that it has a positive influence on the value in Sanggau at time t. At the same time, the value in Sanggau at time t is negatively impacted by the value in Ketapang, Sintang, Landak, and Sekadau at time $t-1$, with each of these values having a coefficient of -0.328.

(3) Sintang.

$$\hat{Z}_{3,t} = -0.068Z_{1,t-1} - 0.068Z_{2,t-1} + 0.531Z_{3,t-1} - 0.068Z_{5,t-1}.$$

With a coefficient of 0.531, the value in Sintang at time t is favourably influenced by the value in Sintang at time $t-1$. This influence is positive. Furthermore, the value in Sintang at time t is negatively influenced by the value in Ketapang, Sanggau, and Sekadau at time $t-1$, with each of these values having a coefficient of -0.068.

(4) Landak.

$$\hat{Z}_{4,t} = 0.265Z_{2,t-1} - 0.372Z_{4,t-1}.$$

At time t, the value in Sanggau at time $t-1$ has a coefficient of 0.265, which indicates that it has a positive influence on the value in Landak at time t. On the other hand, the value in Landak at time $t-1$ has a coefficient of -0.372, which indicates that it has a negative influence.

(5) Sekadau.

$$\hat{Z}_{5,t} = 0.108Z_{1,t-1} + 0.108Z_{2,t-1} + 0.108Z_{3,t-1} - 0.140Z_{5,t-1}.$$

With a coefficient of -0.140, the value in Sekadau at time $t-1$ has a negative influence on the value in Sekadau at time t. This influence is negative. Additionally, the value in Sekadau at time t is favourably influenced by the value in Ketapang, Sanggau, and Sintang at time $t-1$, with each of these values having a coefficient of 0.108.

3.5. *Diagnostic Test of GSTAR Model*

After that, a diagnostic test is performed on the model's residuals. The residual normality test and the residual freedom test are both included in these diagnostic procedures. On the other hand, the residual freedom test is examined using the residual ACF plot, while the residual normality test is evaluated using the Normal Q-Q Plot of residuals. The diagnostic criteria were visually evaluated using these plots. The residuals are considered independent if the lag values in the ACF plot lie within the significance bounds (blue lines). Meanwhile, the residuals are considered normally distributed if the residual data points in the Normal Q–Q plot are scattered around the regression line. Table 3 displays the outcomes of the tests for residual normality and residual freedom performed on each location.

The results of the GSTAR(1;1) model with spatial weights based on rook contiguity are presented in Table 3, and they demonstrate that the model's residuals are distributed equally around the regression line and are within the boundaries of significance. As a result, the GSTAR(1;1) model satisfies the conditions of residual independence and normality. As a result, it is possible to assert that the GSTAR(1;1) model with spatial rook contiguity weights satisfies the assumption of residual white noise.

3.6. *Measurement of Accuracy Level of GSTAR Model*

Following this, the research compares the data obtained from observations and the results obtained from estimations to assess the degree of accuracy possessed by the GSTAR(1;1) model that makes use of spatial weights that are determined by rook contiguity. This step is made to guarantee that the model being used can offer reasonable estimates compared to the actual situation. This is done so that the model can be utilized to assess and predict the number of occurrences of forest fires. The map that can be found below provides a clear depiction of how effectively the GSTAR(1;1) model predicts the frequency of forest fires in the locations that were analyzed. The plot compares the observed data with the estimated findings for each district or city. These graphs make it simpler to see the contrasts and similarities between the data that was seen and the data that the model produced. As a result, they provide a more thorough picture of the correctness of the model.

The estimated data plot is virtually parallel to the observed data plot, as shown in Figure 3, and it follows the observed data plot. As a result, it can be demonstrated that the GSTAR(1;1) model with spatial weights determined by rook contiguity can provide an accurate estimation of the data. The mean Absolute Percentage Error (MAPE) can be used to determine how accurate this model is. The MAPE values for each observed position are presented in Table 4.

According to Table 4, the MAPE value for the five districts and cities is currently at an average of 13%. The fact that the MAPE values fall within this range demonstrates that the GSTAR(1;1) model with spatial rook contiguity weights can produce estimates with a satisfying degree of precision. In this particular setting, the general criteria indicate that a range of 10% to 20% for MAPE can be deemed to be a good level of accuracy.

Table 3: Diagnostic Test of GSTAR Model

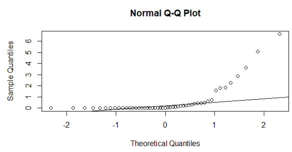
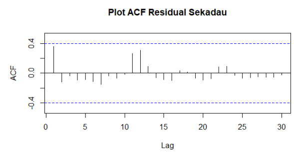
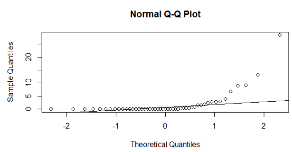
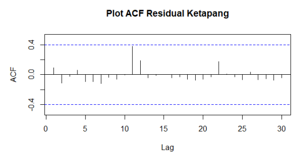
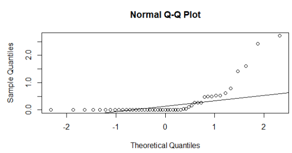
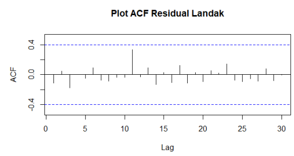
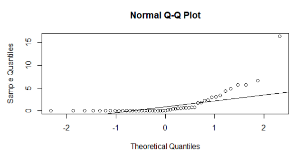
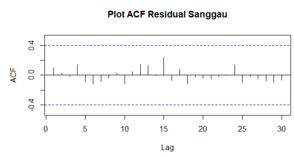
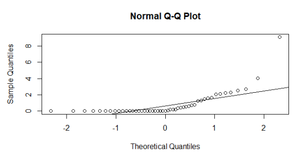
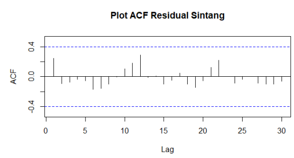
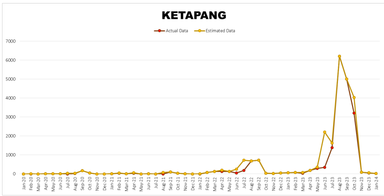
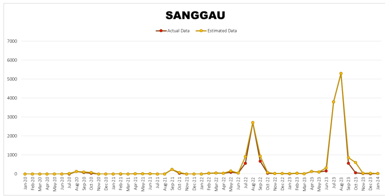
Location	Normal Q-Q Plot Residual	Plot ACF Residual
Ketapang	 Fulfilled	 Fulfilled
Sanggau	 Fulfilled	 Fulfilled
Sintang	 Fulfilled	 Fulfilled
Landak	 Fulfilled	 Fulfilled
Sekadau	 Fulfilled	 Fulfilled

Table 4: MAPE of GSTAR Model

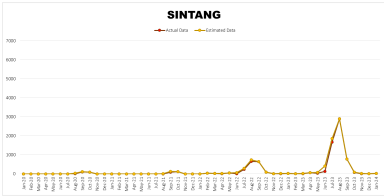
Location	MAPE
Ketapang	19%
Sanggau	16%
Sintang	12%
Landak	5%
Sekadau	13%



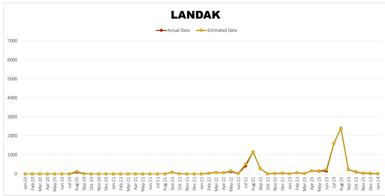
(a)



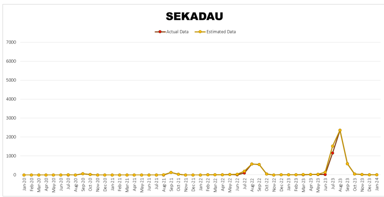
(b)



(c)



(d)



(e)

Figure. 3: Plot of Actual Data and Estimated Data: (a) Ketapang (b) Sanggau (c) Sintang (d) Landak and (e) Sekadau

4. Conclusion

The GSTAR(1;1) model with spatial rook contiguity weights is suitable for application in estimating the number of forest fire cases in five districts/cities in West Kalimantan Province, according to the results and discussion. Additionally, it is possible to conclude that this model is suitable for application. The fact that this model has a Mean Absolute Percentage Error (MAPE) of 13% indicates that it is capable of making forecasts with a good level of accuracy regarding the number of forest fires that will occur in the future. A more in-depth comprehension of the spatial and temporal patterns of forest fires is made possible via the utilization of this model, which also offers a better knowledge of the influence that spatial and temporal elements have on the occurrence of forest fires. A rise in the number of fires in one region can affect the number of fires in other regions, either increasing or decreasing. This spatial pattern demonstrates a substantial link between regions. When there is an increase in the number of fires in Sanggau, for instance, there is a tendency for there to be an increase in the number of fires in Landak. On the other hand, when there is an increase in fires in numerous other regions, there is a tendency for a drop in the number of flames in Sanggau. Depending on the region, the temporal pattern demonstrates that an increase in the number of fire cases can be followed by either an increase or a drop in the number of cases in the period that follows the prior period. Within the context of forest fire prevention and management, this research highlights the significance of improved monitoring and the development of more successful policies. It is envisaged that early warning systems and ways of responding quickly to probable future forest fires can be enhanced via a better understanding of the spatial-temporal patterns of forest fires. For the purpose of addressing forest fires in West Kalimantan, the findings of this research could contribute to the creation of mitigation techniques that are more effective and efficient.

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