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GSTAR (1;1) Modelling with Queen Contiguity for Forest Fire FRP West Kalimantan

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Abstract - Forest fires in West Kalimantan are a recurring problem that causes substantial impacts on the environment and public health. Unlike previous studies that generally focus on hotspot confidence levels or apply distance-based spatial weighting, this study models fire intensity using FRP through a spatial-temporal GSTAR (1;1) approach with a Queen Contiguity neighborhood structure. This approach enables the simultaneous analysis of fire energy dynamics across spatial and temporal dimensions in forest fire–prone areas of West Kalimantan. This study uses FRP data from the NASA FIRMS website, derived from VIIRS on NOAA-20, for the period from July to September 2024. Spatial relationships among neighboring regions are modeled using the Queen Contiguity approach, which considers shared boundaries and vertex connections between regions. The GSTAR (1;1) model can capture both temporal and spatial dependencies in FRP data simultaneously. The analysis results indicate that all model parameters are statistically significant and that the model residuals exhibit white noise characteristics. Model performance evaluation using RMSE, MAPE, and MAD indicates good accuracy: RMSE of 5.693, MAPE of 14.667%, and MAD of 3.165. The similarity between the modeled results and the observed data patterns indicates that the model effectively represents fire intensity conditions. The findings of this study are expected to support more effective data-driven strategies for the prevention and control of forest and peatland fires in West Kalimantan.

***Keywords*:** forest fire, GSTAR, queen contiguity, FRP, spatial-temporal

I. INTRODUCTION

Forest and land fires are recurrent disasters that frequently transpire in Indonesia. This results from the escalating need for land for agricultural pursuits and urban expansion. The primary cause of forest and land fires, particularly in peatland regions, is land conversion, notably for oil palm plantations (Huda et al., 2025). Moreover, a confluence of natural factors, including extended droughts and the El Niño climatic event, alongside anthropogenic actions, such as land clearance by burning, has exacerbated the situation. In peatland regions, the likelihood of fire increases during arid conditions and elevated temperatures, resulting in severe consequences, including ecological degradation, health issues from smoke inhalation, and disruptions to transportation and economic activities (Pratiwi et al., 2025).

The West Kalimantan Province occasionally encounters forest and peatland fires due to its predominance of peatlands situated in the tropical region. Peatland ecosystems can retain biomass, litter, and mineral soil (Ayyash et al., 2025). Forest fires in West Kalimantan are driven by deforestation and land-use changes that exacerbate these conditions (Awaluddin et al., 2024). Figure 1 (see Appendices) shows that West Kalimantan had the highest number of forest and land fire hotspots among all Indonesian provinces in 2024, according to data sourced from the official website of the Ministry of Environment and Forestry (sipongi.menlhk.go.id, 2025). These incidents frequently exert extensive local and transnational effects, as the emitted smoke can compromise air quality in adjacent regions (Kala, 2023). Fire patterns are significantly influenced by spatial factors, including vegetation type and topography, as well as temporal factors such as the dry season and meteorological conditions (Zhao et al., 2021).

The utilisation of the Generalized Space-Time Autoregressive (GSTAR) model is pertinent for comprehending the dynamics of forest fires in West Kalimantan. This model enhances the understanding of fire patterns and trends, facilitating more efficient risk management and mitigation strategies. West Kalimantan, recognised for its vast peatlands and tropical forests, faces significant issues related to forest fires (Maswadi et al., 2020). Alongside natural reasons, the practice of land burning for agriculture and alterations in land use further exacerbate the frequency and intensity of fires.

The GSTAR model integrates autoregressive components of time series data with spatial interdependencies among locations (Imro'ah & Huda, 2025). This method enables the model to account for the impact of geographically proximate places while identifying temporal trends that Influence the value of a variable in subsequent periods (Munandar et al., 2023). The occurrence pattern of forest fires is significantly influenced by spatial factors, including vegetation type, topography, and geographic location, as well as temporal factors such as the dry season and meteorological conditions. Consequently, the application of the GSTAR model is deemed suitable for examining fire propagation, particularly in West Kalimantan.

The Fire Radiative Power (FRP) value can be used to discern forest and land fire indicators. FRP is a metric that quantifies the radiation power emitted by fire pixels and is expressed in Megawatts (MW) (Fu et al., 2020). FRP conveys data regarding the quantity of thermal energy the identified fire releases. The rate of heat radiation energy emitted per unit of time is directly correlated with fuel consumption, specifically the quantity of biomass or organic Material combusted during the fire event (Kusuma et al., 2023). From July to September 2024, the districts of Sanggau, Ketapang, and Sintang in West Kalimantan had the highest concentration of forest and land fire hotspots among the province's districts.

Previous studies on forest fires have used spatial-temporal models such as GSTAR; however, they generally relied solely on hotspot confidence levels as indicators of fire intensity, which do not provide continuous information about fire energy. Unlike previous studies, this Research models fire intensity using FRP via a first-order spatial-temporal GSTAR (1;1) with a Queen Contiguity spatial weight structure. This approach enables the simultaneous analysis of fire dynamics across both spatial and temporal dimensions in fire-prone areas of West Kalimantan. The GSTAR (1;1) model captures spatial and temporal dynamics simultaneously, enabling a more comprehensive description of FRP fluctuations over time. FRP values are influenced not only by the previous time step ($t-1$) but also by geographically adjacent locations (Huda et al., 2023).

Modeling with the Queen Contiguity spatial weight matrix considers the interrelations among locations based on horizontal, vertical, and diagonal proximity (Sedubun et al., 2023). This matrix effectively represents spatial relationships among neighboring areas, thereby improving the accuracy of FRP predictions for each analyzed district. The appropriate selection of a spatial weight matrix, combined with a better understanding of spatial-temporal relationships, is expected to produce more accurate predictions. Insights gained from this analysis are crucial for designing effective fire management strategies and supporting more sustainable environmental management policies in the future.

Research related to spatial–temporal modelling using the GSTAR approach has been widely conducted across various fields. According to Mukhaiyar et al. (2024), the importance of the spatial weight matrix in GSTAR modelling was emphasized, and the Minimum Spanning Tree (MST) approach was proposed to reduce subjectivity in weight construction (Mukhaiyar, Mahdiyasa, Sari, et al., 2024). Mukhaiyar et al. (2024) stated that "the GSTAR(2;1,1) model with an MST-based spatial weight matrix produced the best forecasting performance based on RMSE and MAPE values". Another study by Huda and Imro'ah (2024) applied the GSTAR(1;1) model to model the spread of COVID-19 cases across 41 districts/cities on Java Island using the Queen Contiguity weight matrix (Huda & Imro'ah, 2024). Huda and Imro'ah (2024) stated that "the GSTAR(1;1) model was able to capture spatial interactions between regions and temporal dependence, and successfully generated five-period-ahead predictions for all observation locations".

Research related to forest fire analysis was conducted by Pratiwi et al. (2025), who utilized a spatial–temporal GSTAR model combined with the Queen Contiguity weight matrix to model hotspot confidence levels in West Kalimantan (Pratiwi et al., 2025). Pratiwi et al. (2025) stated that "the GSTAR(3;1) model satisfied the white-noise assumption and achieved a MAPE value of 14.78%, indicating reasonably accurate short-term predictions of hotspot confidence levels". Meanwhile, Research focusing on Fire Radiative Power (FRP) was conducted by Fu et al. (2020), who compared MODIS and VIIRS satellite fire products in Northeast Asia (Fu et al., 2020). Fu et al. (2020) stated that "VIIRS detected more fire pixels and higher total FRP than MODIS, particularly in low-biomass lands, due to lower omission errors".

II. METHODS

The GSTAR (1;1) model is a generalization of the spatial-temporal autoregressive model that simultaneously accommodates spatial and temporal dependencies. This model includes one temporal lag and one spatial lag. The first-order spatial lag represents the Influence of directly neighboring locations. In contrast, the first-order temporal lag indicates that the value of a variable at time t is influenced by its value at the previous time period ($t-1$) at the same location

(Huda et al., 2023). Spatial dependence in this model is expressed through the spatial weight matrix W ,which represents interregional relationships based on geographic proximity, including horizontal, vertical, and diagonal adjacency.

The GSTAR model was first introduced by Borovkova, Lopuha, and Ruchjana in 2002 as an extension of the Autoregressive (AR) and Space-Time Autoregressive (STAR) models. This development aimed to enable the analysis of time series that are influenced not only by temporal factors but also by spatial variations across locations. By integrating these two aspects, the GSTAR (1;1) model can be systematically applied to spatio-temporal data modeling. The model has been widely employed in environmental studies, forest fire Research, epidemiology, regional economics, and other spatio-temporal phenomena. Furthermore, by incorporating a first-order temporal lag, the model accounts for the variable's value in the previous period ($t-1$) as a determinant of its value in the current period (t) (Pasaribu et al., 2022). Mathematically, the GSTAR (1;1) model can be expressed as follows (Ayyash et al., 2025).

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

where Y_t represents the observations at time t, Y_{t-1} denotes the observations at time ($t-1$), Φ_{10} is the autoregressive coefficient capturing the influence of the location itself, Φ_{11} is the autoregressive coefficient reflecting the influence of neighboring locations, $W_{(*)}$ is the weight matrix, e_t is the error term at time t. Alternatively, the GSTAR(1;1) model in Equation (1) can be expressed in its matrix form as follows (Equation 2).

The GSTAR(1;1) model is designed to capture both temporal dynamics and spatial interactions across regions, which requires incorporating a structured framework to represent spatial dependence. The spatial weight matrix is a crucial element in the GSTAR model, representing the interrelationships between places in spatial dimensions (Utami et al., 2024). This matrix assesses the degree to which one site influences another based on geographic proximity, namely the physical distance between them. In forest fire analysis, each matrix element indicates the degree of interaction between locations. The spatial weight matrix must satisfy the following conditions: $w_{ii} = 0$, and $\sum_{i\neq j} w_{ii} = 1$ for $i = 1, 2, ..., N$ and $j = 1, 2, ..., N$ (Mukhaiyar, Mahdiyasa, Prastoro, et al., 2024). The spatial weight matrix is often represented as a square matrix of dimensions $N \times N$, denoted as $W^{(\ell)}$. Equation (2) defines the general form of the spatial weight matrix, where W_{ij} is the weight between regions j and i (Pratiwi et al., 2025).

Among the numerous spatial weight matrices, Queen Contiguity is often used in the GSTAR model to model the link between sites based on geographic proximity. This idea defines two locations as neighbors if they share a border, whether horizontal, vertical, or diagonal (Tsanawafa et al., 2024). The analogy resembles the movement of the "Queen" piece in chess, which can traverse in any direction. In this matrix, pairs of nearby places receive a weight of 1, whereas non-adjacent locations receive a weight of 0 (Pratiwi et al., 2025). Normalization of the matrix is necessary to get the value of $\sum_{i\neq j} w_{ii} = 1$, using Equation (3) as follows:

$$\boldsymbol{W}^{(\ell)} = \left[\frac{\boldsymbol{w}_{ij}^{(\ell)}}{\boldsymbol{w}_{i}^{(\ell)}}\right]_{N\times N} \qquad (3)$$

where w_{ij} denotes the weight of location j relative to location i, and w_i represents the total weight of all locations relative to location i.

Figure 2 (see Appendices) illustrates the spatial weight structure constructed using the Queen Contiguity approach for 14 districts in West Kalimantan. The dark blue areas and black circles represent the study area, while the white regions with numerical labels indicate the neighboring districts.

Within the GSTAR framework, the Queen Contiguity spatial weight matrix is employed to delineate spatial dependencies across regions, thereby providing a structural basis for subsequent parameter estimation. The Ordinary Least Squares (OLS) method is applied to estimate the parameters of the GSTAR model. This estimation approach is selected because it effectively minimizes the sum of squared prediction errors. Consequently, OLS can be utilized to estimate

$$\begin{bmatrix} Y_t^{(1)} \\ Y_t^{(2)} \\ \vdots \\ Y_t^{(N)} \end{bmatrix} = \begin{bmatrix} \phi_{10}^{(1)} & 0 & \cdots & 0 \\ 0 & \phi_{10}^{(2)} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \phi_{10}^{(N)} \end{bmatrix} \begin{bmatrix} Y_{(t-1)}^{(1)} \\ Y_{(t-1)}^{(2)} \\ \vdots \\ Y_{(t-1)}^{(N)} \end{bmatrix} + \begin{bmatrix} \phi_{11}^{(1)} & 0 & \cdots & 0 \\ 0 & \phi_{11}^{(2)} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \phi_{11}^{(N)} \end{bmatrix} \begin{bmatrix} 0 & w_{12}^{(\ell)} & \cdots & w_{1N}^{(\ell)} \\ w_{21}^{(\ell)} & 0 & \cdots & w_{2N}^{(\ell)} \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1}^{(\ell)} & w_{N1}^{(\ell)} & \cdots & 0 \end{bmatrix} \begin{bmatrix} Y_{(t-1)}^{(1)} \\ Y_{(t-1)}^{(2)} \\ \vdots \\ Y_{(t-1)}^{(N)} \end{bmatrix} + \begin{bmatrix} \boldsymbol{e}_t^{(1)} \\ \boldsymbol{e}_t^{(2)} \\ \vdots \\ \boldsymbol{e}_t^{(N)} \end{bmatrix}$$

$$\boldsymbol{W}^{(\ell)} = [w_{ij}^{(\ell)}] = \begin{bmatrix} 0 & w_{12}^{(\ell)} & \cdots & w_{1N}^{(\ell)} \\ w_{21}^{(\ell)} & 0 & \cdots & w_{2N}^{(\ell)} \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1}^{(\ell)} & w_{N1}^{(\ell)} & \cdots & 0 \end{bmatrix} \qquad (2)$$

where w_{ij} is the weight between regions j and i.

the parameters of the GSTAR(1;1) model and improve the accuracy of forecasting results, Provided that $t = 2, 3, \ldots T$ and $V_{(t-1)}^{(i)} = \sum_{j=1}^{N} w_{ij} Y_{(t-1)}^{(j)}$ for $i \neq j$. In general, the OLS method can be expressed as shown in Equation (4) (Hestuningtias & Kurniawan, 2023).

$$Y = X\Phi + e \tag{4}$$

where $\boldsymbol{Y} = \begin{bmatrix} Y_t^{(1)} \\ Y_t^{(2)} \\ \vdots \\ Y_t^{(N)} \end{bmatrix}$; $\boldsymbol{\Phi} = \begin{bmatrix} \phi_{10}^{(1)} \\ \phi_{11}^{(1)} \\ \phi_{10}^{(2)} \\ \phi_{11}^{(2)} \\ \vdots \\ \phi_{10}^{(N)} \\ \phi_{11}^{(N)} \end{bmatrix}$; $\boldsymbol{e} = \begin{bmatrix} \boldsymbol{e}_t^{(1)} \\ \boldsymbol{e}_t^{(2)} \\ \vdots \\ \boldsymbol{e}_t^{(N)} \end{bmatrix}$;

$$\boldsymbol{X} = \begin{bmatrix} Y_{(t-1)}^{(1)} & V_{(t-1)}^{(1)} & 0 & 0 & \cdots & \cdots & 0 & 0 \\ 0 & 0 & Y_{(t-1)}^{(2)} & V_{(t-1)}^{(2)} & \cdots & \cdots & 0 & 0 \\ 0 & 0 & 0 & 0 & \ddots & \ddots & 0 & 0 \\ 0 & 0 & 0 & 0 & \cdots & \cdots & Y_{(t-1)}^{(N)} & V_{(t-1)}^{(N)} \\ 0 & 0 & 0 & 0 & & & & \end{bmatrix}$$

Equation (5) can therefore be applied to estimate the parameters of the GSTAR (1;1) model.

$$\widehat{\boldsymbol{\Phi}} = [\boldsymbol{X}^T\boldsymbol{X}]^{-1}[\boldsymbol{X}^T\boldsymbol{Y}] \tag{5}$$

III. RESULTS AND DISCUSSIONS

Data preprocessing is conducted prior to constructing the GSTAR model to ensure the data is prepared for analysis and that the model's underlying assumptions are met. This analysis utilizes daily FRP data, measured in MegaWatts (MW), derived from the fire radiation emitted by hotspots, obtained from the NASA FIRMS (Fire Information for Resource Management System) website (NASA-FIRMS, 2025). According to the monthly hotspot data presented in Figure 3 (see Appendices), the period from July to September 2024 was the peak of forest fires in West Kalimantan, with a substantial increase in the number of hotspots compared to other months.

The regencies of Sanggau, Ketapang, and Sintang were selected because they had the highest number of hotspots from July to September 2024. The three regencies rank highest for the number of hotspots per district or city, as illustrated in Figure 4 (see Appendices). The distribution data and the quantity of documented hotspots solely determined the selection of the study period and location.

The first step is to filter the data by geographical area, as it encompasses the entire country of Indonesia. Following data preprocessing, a total of 92 days of observation were compiled, encompassing hotspot data characterized by Fire Radiative Power (FRP). This study specifically focuses on three regencies in West Kalimantan: Sanggau, Ketapang, and Sintang. Consequently, data sorting is performed based on latitude and longitude coordinates that align with West Kalimantan administrative boundaries. Figure 5 (see Appendices) illustrates this technique.

During data preprocessing, summary statistics were computed to provide a preliminary overview of the dataset before proceeding with model estimation. Figure 6 (see Appendices) presents the descriptive statistics for the data used in the GSTAR modeling. The presented data encompasses the minimum, maximum, and average values for each analyzed district.

Figure 6 (see Appendices) displays the descriptive statistics of FRP data over a 92-day observation period. The statistics demonstrate that peak fire incidents occur on specific days. Sanggau Regency reported the highest maximum FRP value of 252.09 MW on September 16, 2024, followed by Ketapang at 193.07 MW on September 12, 2024, and Sintang at 182.37 MW on September 7, 2024. The maximum average FRP value was observed in Ketapang Regency at 33.55 MW, whereas the minimum was noted in Sintang Regency at 25.33 MW.

Following the descriptive statistical analysis, it is necessary to assess the data's fundamental properties to ensure the robustness and validity of the modeling process. The stationarity test is a crucial step prior to time series modeling. Stationarity denotes the statistical constancy of data, including mean and variance, which remain unchanged across time. Data is considered steady if its variations are centered around the mean with a constant variance (Pusporani et al., 2024).

The Augmented Dickey-Fuller (ADF) and Box-Cox tests are employed to ascertain the stationarity of the dataset (Roza et al., 2022). The graphical representation in Figure 7 (see Appendices) shows that the series remains stable with respect to both the mean and the variance. This finding provides preliminary evidence that the data satisfy the basic requirements for further time-series and spatial-temporal modeling. The ADF test is used to verify the data's true stationarity. The test findings indicate that the p-value for Sanggau, Ketapang, and Sintang Regencies is 0.01, signifying that it is below 0.05. Consequently, the three Regencies possess static data.

Upon confirmation of the data's stationarity, the subsequent procedure entails examining and specifying the spatial dependence structure. Queen Contiguity will be employed for the subsequent phase in computing the weight matrix. The application of the Queen Contiguity rule to the three established locations is illustrated in the surrounding environment depicted in Figure 8 (see Appendices).

Figure 8 (see Appendices) illustrates the Queen Contiguity Map for the Sanggau, Ketapang, and Sintang Regencies. Figure (a) presents the spatial configuration of the three regions. Figures (b), (c), and (d) show the Queen contiguity representation for Sanggau, Ketapang, and Sintang, respectively. In these figures, a value of 1 indicates neighboring regions, while 0 indicates the region itself. Table 1 presents the Queen Contiguity weight matrix, illustrating the spatial relationships among Sanggau, Ketapang, and Sintang. These weights were computed according to the Queen Contiguity method as defined in Equation (2), and the normalized values ensuring that the sum of each row equals one were obtained following Equation (3).

Table 1 Queen Contiguity Weight Matrix

Weight	Before Normalization	After Normalization
$W^{(0)}$	**I**, identity matrix of size $N \times N$	
$W^{(1)}$	$\begin{bmatrix} 0 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \end{bmatrix}$	$\begin{bmatrix} 0 & 0.5 & 0.5 \\ 0.5 & 0 & 0.5 \\ 0.5 & 0.5 & 0 \end{bmatrix}$

Based on the spatial structure specified by the Queen Contiguity weight matrix, the parameters were subsequently estimated within the GSTAR(1;1) framework as formulated in Equation (5). Table 2 presents the estimated parameters obtained from the application of the GSTAR(1;1) model to the FRP data. Parameter estimation was carried out using the Ordinary Least Squares (OLS) estimator as defined in Equation (4), and the location-specific coefficients were computed following Equation (5). Furthermore, the statistical significance of each estimated parameter was examined using parameter significance tests at the 1% significance level ($\alpha = 0.01$). These results reflect the temporal and spatial dependencies among the three regencies in West Kalimantan Province and provide a basis for evaluating model adequacy and interpreting the spatial interactions embedded in the data.

Table 2 Parameter Estimation

Loksi	Parameter			
	$\hat{\Phi}_{10}$	Sig.	$\hat{\Phi}_{11}$	Sig.
Sanggau	0.118	Yes	−0.146	Yes
Ketapang	0.156	Yes	−0.054	Yes
Sintang	0.108	Yes	−0.233	Yes

After parameter estimation and significance testing, the model's adequacy was assessed to ensure that the underlying assumptions were met. Following the estimation process and parameter significance evaluation, a model suitability assessment was conducted to verify adherence to the model conditions. The results of the white-noise residual diagnostic tests for each site in the GSTAR(1;1) model indicate that the residuals satisfy both the independence and normality assumptions, thereby supporting the model's validity.

A crucial phase in evaluating a model's quality is the diagnostic testing stage, which is conducted to verify that the developed model meets the criteria for practical suitability and delivers reliable forecasting outcomes. A model is considered acceptable if its residuals satisfy the white noise condition, namely, they are random, independent, and normally distributed. Adherence to these assumptions is an essential measure of the model's predictive reliability and accuracy (Hassani et al., 2025).

In this study, the independence of residuals was examined using the autocorrelation function (ACF), while residual normality was assessed using a Q–Q plot. According to Table 3, the model developed using the Queen Contiguity weight matrix satisfies the white noise assumption. This indicates that the model is appropriate for predicting the FRP values of forest and land fires in the Sanggau, Ketapang, and Sintang Regencies.

After completing residual diagnostic tests, the next step is to assess the model's predictive performance. To assess the accuracy of the forecasting model, many methodologies are typically employed to quantify prediction error. Examples are Mean Absolute Deviation (MAD), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) (Amar et al., 2020). MAPE evaluates model accuracy by computing the average absolute percentage error between the actual and estimated values. A lower MAPE value indicates higher model accuracy in forecasting observational data (Jierula et al., 2021). RMSE, the square root of MSE, quantifies the accuracy of forecasts relative to historical data, with lower RMSE values indicating superior predictive performance (Chicco et al., 2021). Meanwhile, the Mean Absolute Deviation (MAD) quantifies the average absolute error regardless of the direction of the discrepancy, assigning equal weight to all discrepancies between the forecasted and actual values (Elamir, 2025). The values of these three error metrics are utilized to evaluate the correctness of the GSTAR (1;1) model in each district, as shown in Table 4 below.

Based on the model accuracy levels indicated by the RMSE, MAPE, and MAD values of 5.693, 14.667%, and 3.165, respectively, across the regencies, it can be concluded that the GSTAR(1;1) model demonstrates satisfactory predictive capability. The model presented in Table 3 indicates that the GSTAR(1;1) model with the Queen Contiguity weight matrix can be expressed as follows. The parameter estimates of the GSTAR(1;1) model for Sanggau, Ketapang, and Sintang Regencies are presented in Equations (6)–(8), which are derived from the general model structure formulated in Equation (1). These equations represent the temporal dependence of each region on its own historical values as well as the

Table 3 Model Diagnostic Test

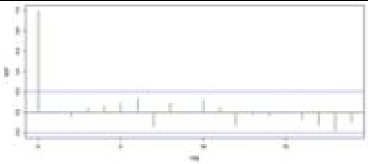
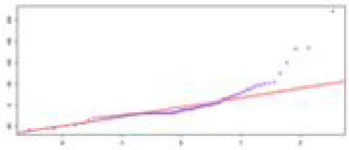
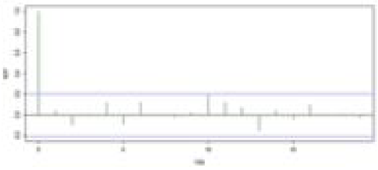
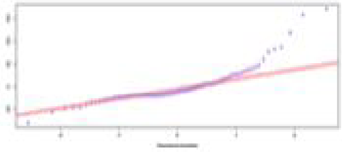
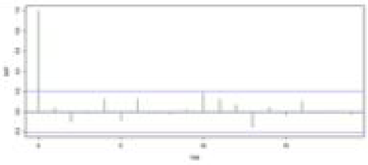
Location	Diagnostic Test		Information
	Independence	Normality	
Sanggau			White Noise
Ketapang			White Noise
Sintang			White Noise

Table 4 GSTAR (1;1) Model Accuracy

RMSE	MAPE (%)	MAD
5.693	14.667	3.165

spatial Influence of neighboring regions. Specifically, Equation (6) describes the dynamics of Sanggau Regency, Equation (7) corresponds to Ketapang Regency, and Equation (8) characterizes Sintang Regency.

$$Y_t^{(1)} = 0.118\, Y_{t-1}^{(1)} - 0.073\, Y_{t-1}^{(2)} - 0.073\, Y_{t-1}^{(3)} \tag{6}$$

$$Y_t^{(2)} = 0.016\, Y_{t-1}^{(1)} - 0.027\, Y_{t-1}^{(2)} - 0.027\, Y_{t-1}^{(3)} \tag{7}$$

$$Y_t^{(3)} = 0.108\, Y_{t-1}^{(1)} - 0.117\, Y_{t-1}^{(2)} - 0.117 Y_{t-1}^{(3)} \tag{8}$$

The estimation results of the GSTAR(1;1) model indicate the presence of both spatial and temporal dependence among the three observed regions, namely Sanggau, Ketapang, and Sintang Regencies. In Sanggau Regency, the FRP value at a given time is primarily influenced by the FRP value at the same location in the previous period, with an estimated coefficient of 0.118. Meanwhile, the influences of Ketapang and Sintang Regencies on Sanggau Regency are −0.073 each, indicating negative effects of relatively small magnitude. This suggests that increases in FRP values in neighboring regencies tend to be followed by slight decreases in Sanggau Regency in the subsequent period. In Ketapang Regency, the FRP value is influenced by Sanggau Regency, with a coefficient of 0.016, whereas the effects of Ketapang Regency and Sintang Regency are −0.027 and −0.027, respectively. Furthermore, in Sintang Regency, the FRP value is influenced by previous FRP values from Sanggau Regency (0.108) and Ketapang Regency (−0.117).

These findings indicate that although multiple regions contribute to the dynamics of Fire Radiative Power (FRP), Sanggau Regency exerts a stronger Influence than the other regions. Overall, the results confirm spatial interdependence among the three regencies, with Sanggau Regency playing an important role in shaping forest fire dynamics in the surrounding areas. The negative parameter estimates obtained in the GSTAR(1;1) model used to predict FRP in the study area can be explained by the Influence of seasonal factors that affect forest fire occurrence patterns. For example, a regency may experience relatively high FRP values during the dry season, followed by a decline in the subsequent period when the rainy season begins, leading to negative parameter coefficients in the model.

Figure 9 (see Appendices) presents a comparison between the actual data and the model-generated forecasts to illustrate the performance of the GSTAR(1;1) model, with panels (a), (b), and (c) corresponding to Sanggau, Ketapang, and Sintang Regencies, respectively. In each plot, the blue line represents the actual FRP data, while the orange line denotes the model-predicted FRP values. The visual comparison indicates that the predicted values generally follow the pattern of the actual data across the three regencies, although minor deviations are observed in certain observation periods. This pattern consistency suggests that the model captures the temporal variation in FRP values with adequate accuracy. Therefore, these results indicate that the GSTAR(1;1) model with the Queen Contiguity weight matrix is appropriate for forecasting forest fire occurrences in West Kalimantan.

IV. CONCLUSIONS

The results indicate that the GSTAR (1;1) model with a Queen Contiguity spatial weight matrix, using daily FRP data from Sanggau, Ketapang, and Sintang Regencies during July–September 2024, is capable of effectively modeling and forecasting FRP values associated with forest fire events in West Kalimantan. The spatial weight matrix represents the spatial relationships among neighboring regions. Parameter estimation results show that interregional interactions significantly Influence FRP dynamics, with Sanggau Regency exhibiting a more dominant effect, while negative parameter values reflect seasonal effects in forest fire patterns. The model demonstrates good performance, as indicated by an RMSE of 5.693, a MAPE of 14.667%, and a MAD of 3.165. Furthermore, the comparison between actual and predicted values shows consistent agreement across all study regions.

This study has several limitations that should be acknowledged. First, the spatial coverage is limited to only three regencies, which may limit the generalizability of the results to other areas in West Kalimantan. Second, the relatively short observation period may constrain the model's ability to capture seasonal variations or long-term trends. Third, the use of a single Queen Contiguity spatial weight matrix without incorporating exogenous variables restricts the understanding of external factors, such as climatic conditions, that may Influence the dynamics of forest fires.

Future Research is recommended to expand the study area to include more regencies or other regions and to employ a longer observation period to capture seasonal patterns and long-term trends more accurately. In addition, comparing multiple spatial weighting schemes and incorporating exogenous variables, such as rainfall and air temperature, are expected to enhance the model's ability to explain variations in FRP and to provide a more comprehensive understanding of the factors influencing forest fire occurrences.

AUTHOR CONTRIBUTIONS

Conceived and designed the analysis, Z., N. M. H., N. I. and G. F.; Collected the data, Z. and G. F.; Contributed data or analysis tools, N. M. H., N. I. and G. F.; Performed the analysis, Z., N. M. H. and N. I.; Wrote the paper, Z.

DATA AVAILABILITY

Data derived from public domain resources. The data that support the findings of the research are available in NASA FIRMS at https://firms.modaps.eosdis.nasa.gov/ , reference number [not applicable]. These data were derived from the following resources available in the public domain: [NASA FIRMS (Fire Information for Resource Management System), accessible at https://firms.modaps.eosdis.nasa.gov/].

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APPENDICES

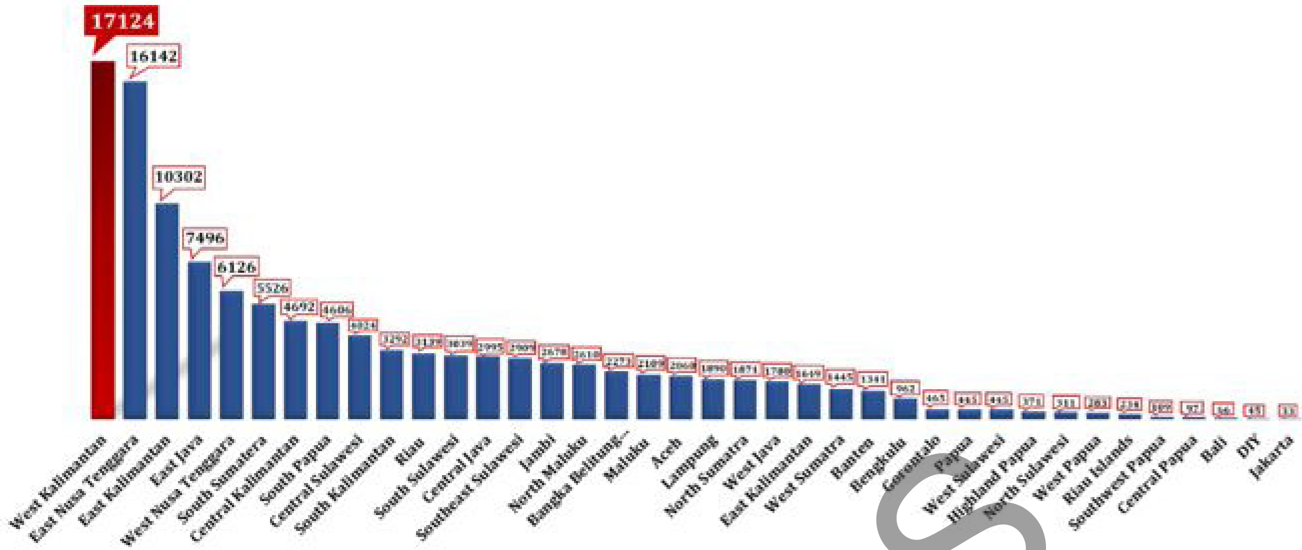


Figure 1 Number of Forest and Land Fire Hotspots by Province in Indonesia in 2024

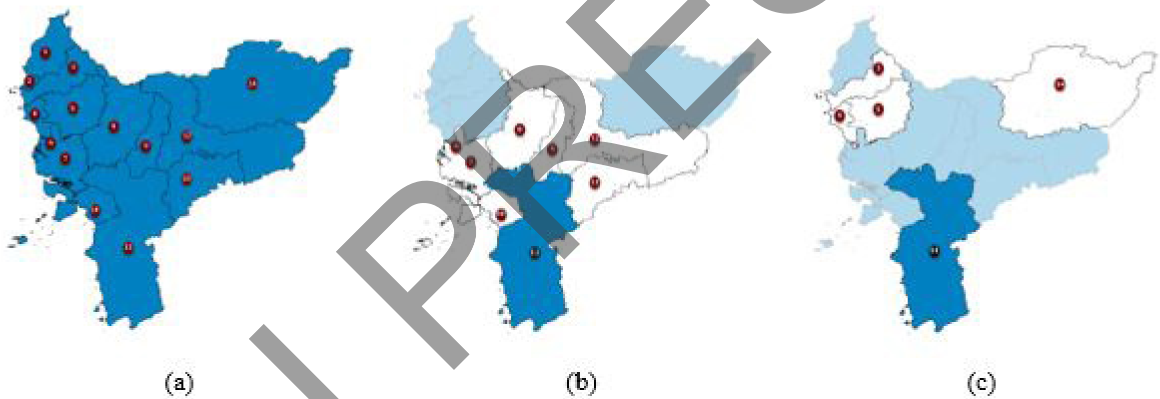


Figure 2 Queen Contiguity Weight Illustration: (a) study area, (b) first-order neighbors and (c) second-order neighbors

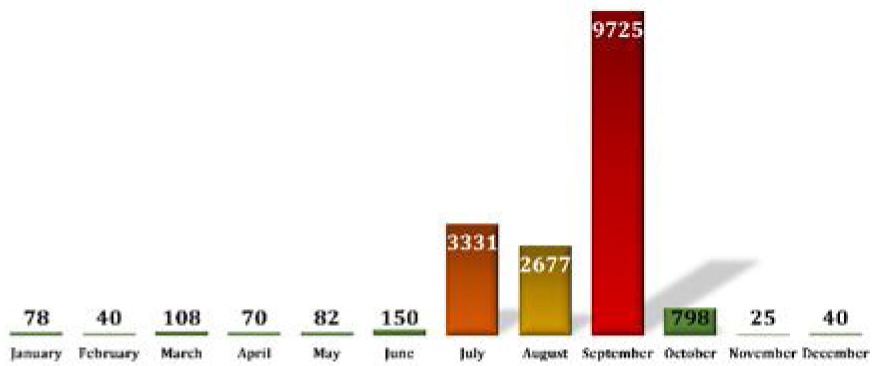


Figure 3 Monthly Number of Hotspots in West Kalimantan in 2024

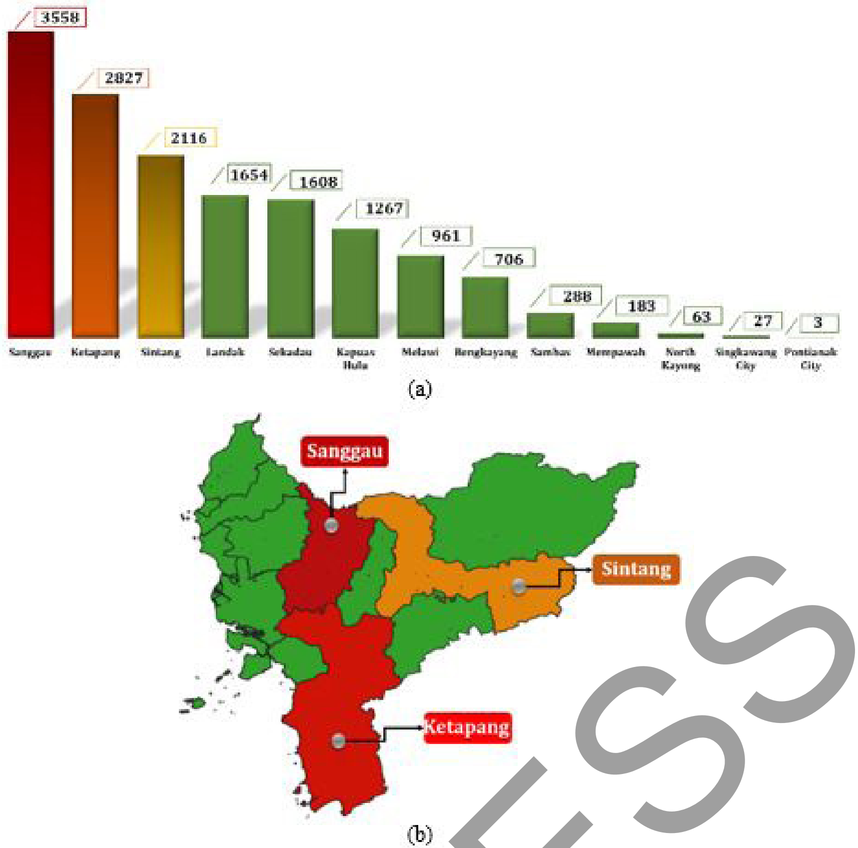


Figure 4 (a) Number and (b) of Cases of Forest Fires in West Kalimantan 2024

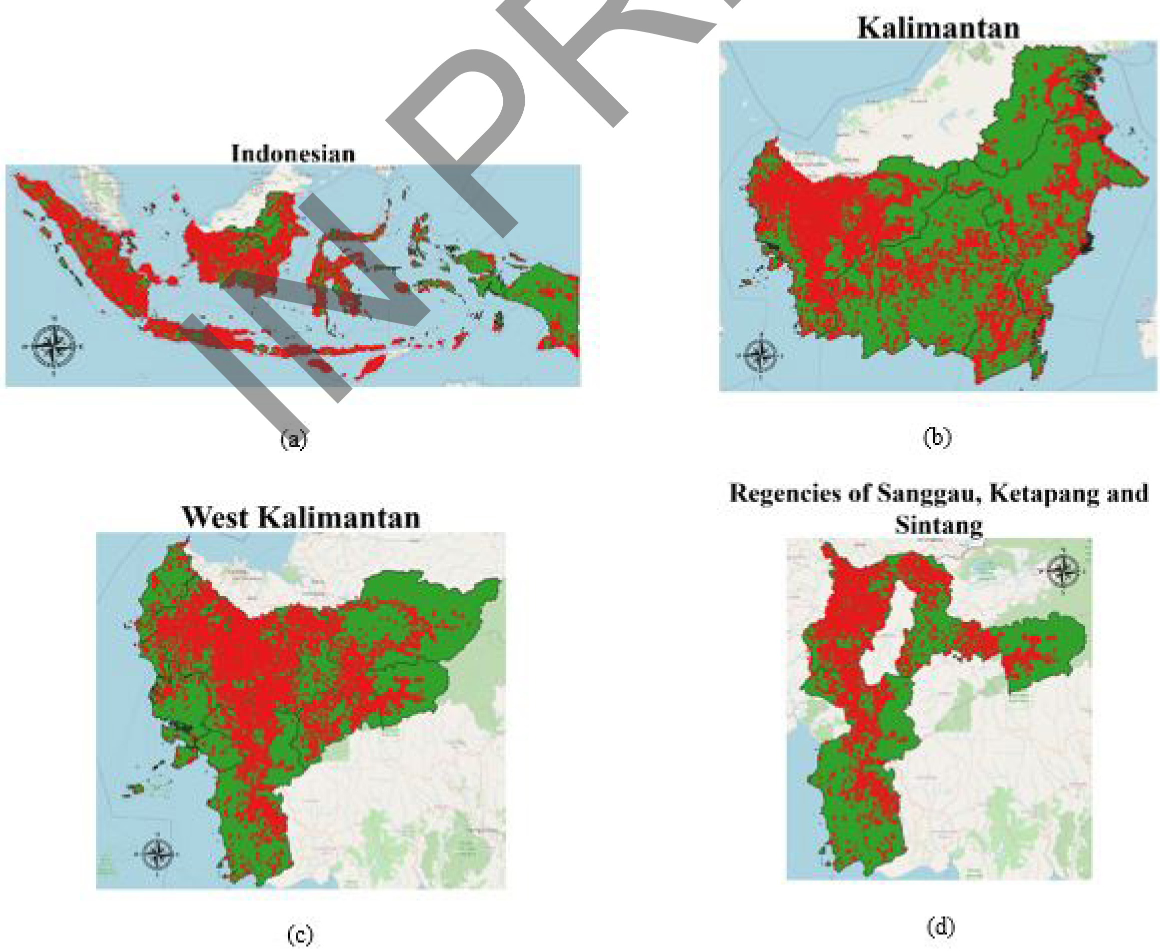
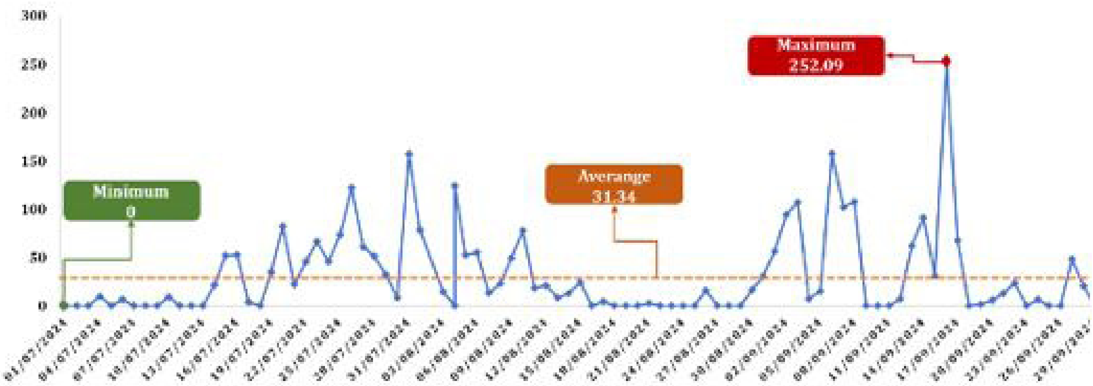
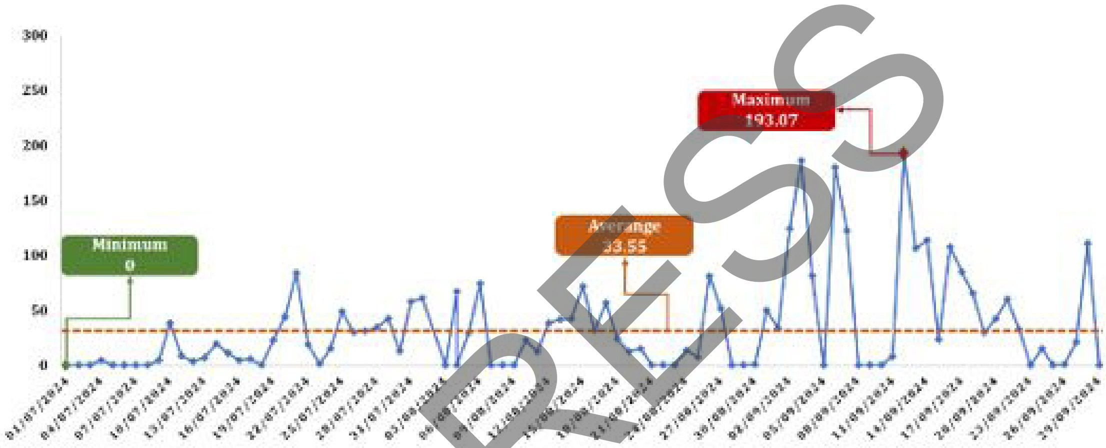


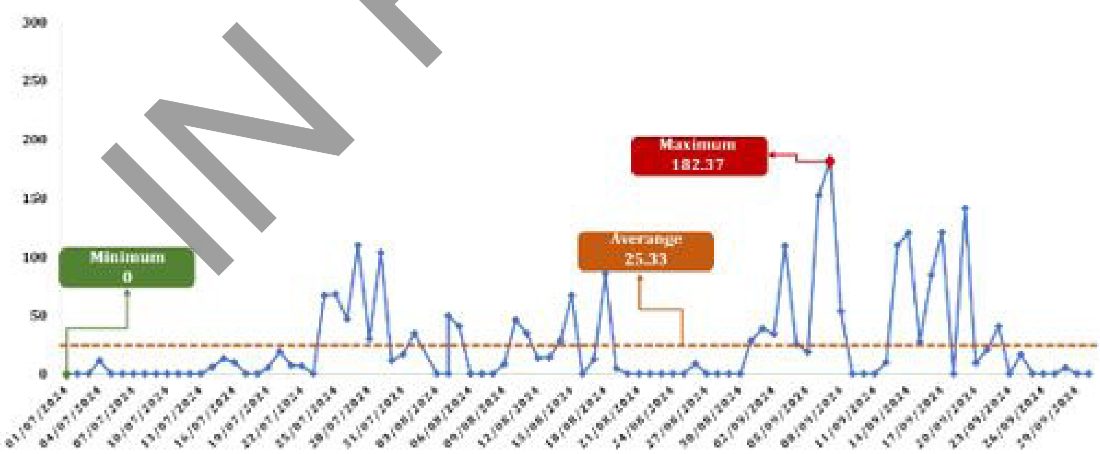
Figure 5 illustrates the data filtering process of hotspot observations: (a) Indonesian, (b) Kalimantan, (c) West Kalimantan, and (d) the regencies of Sanggau, Ketapang, and Sintang.



(a)

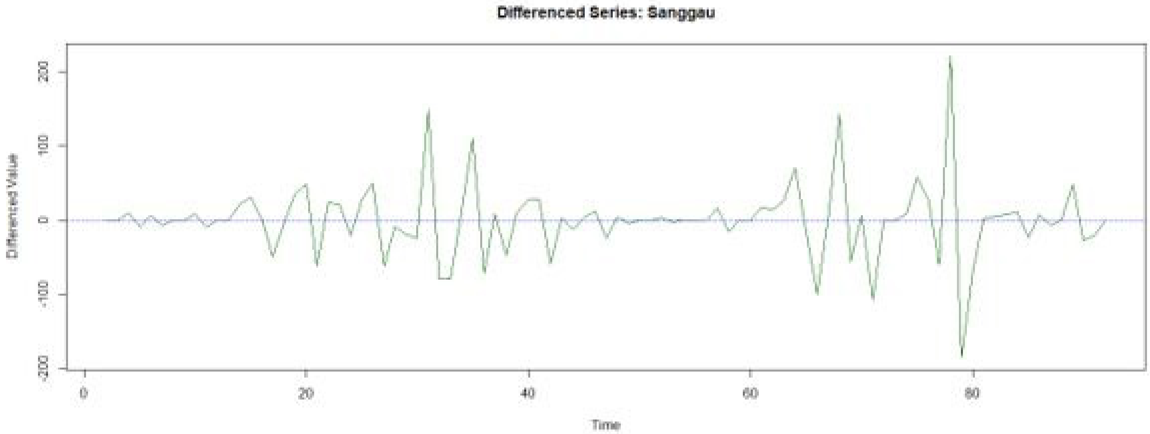


(b)



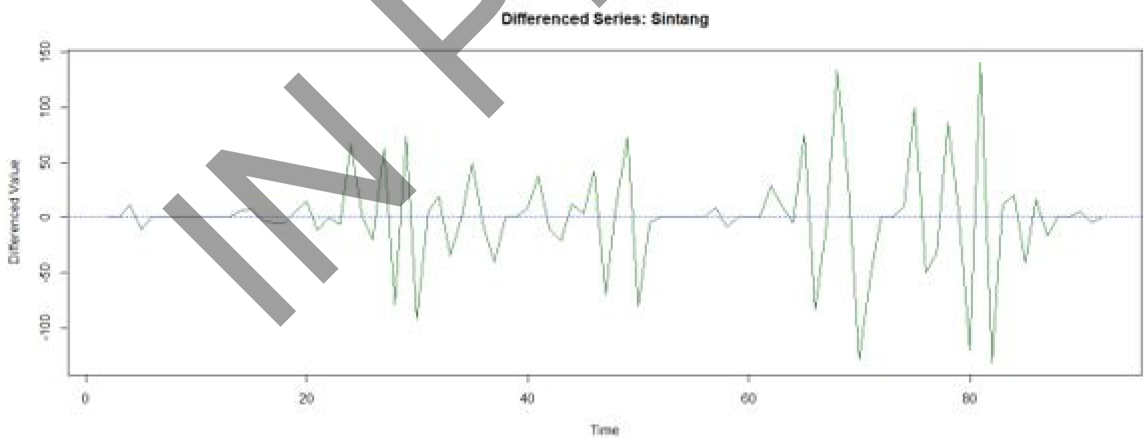
(c)

Figure 6 Descriptive Statistics of Fire Radiative Power (FRP) Data:
(a) Sanggau (b) Ketapang and (c) Sintang, measured in Megawatts (MW).



(a)

(b)



(c)

Figure 7 Data Stationarity in Three Regencies of West Kalimantan:
(a) Sanggau (b) Ketapang (c) Sintang

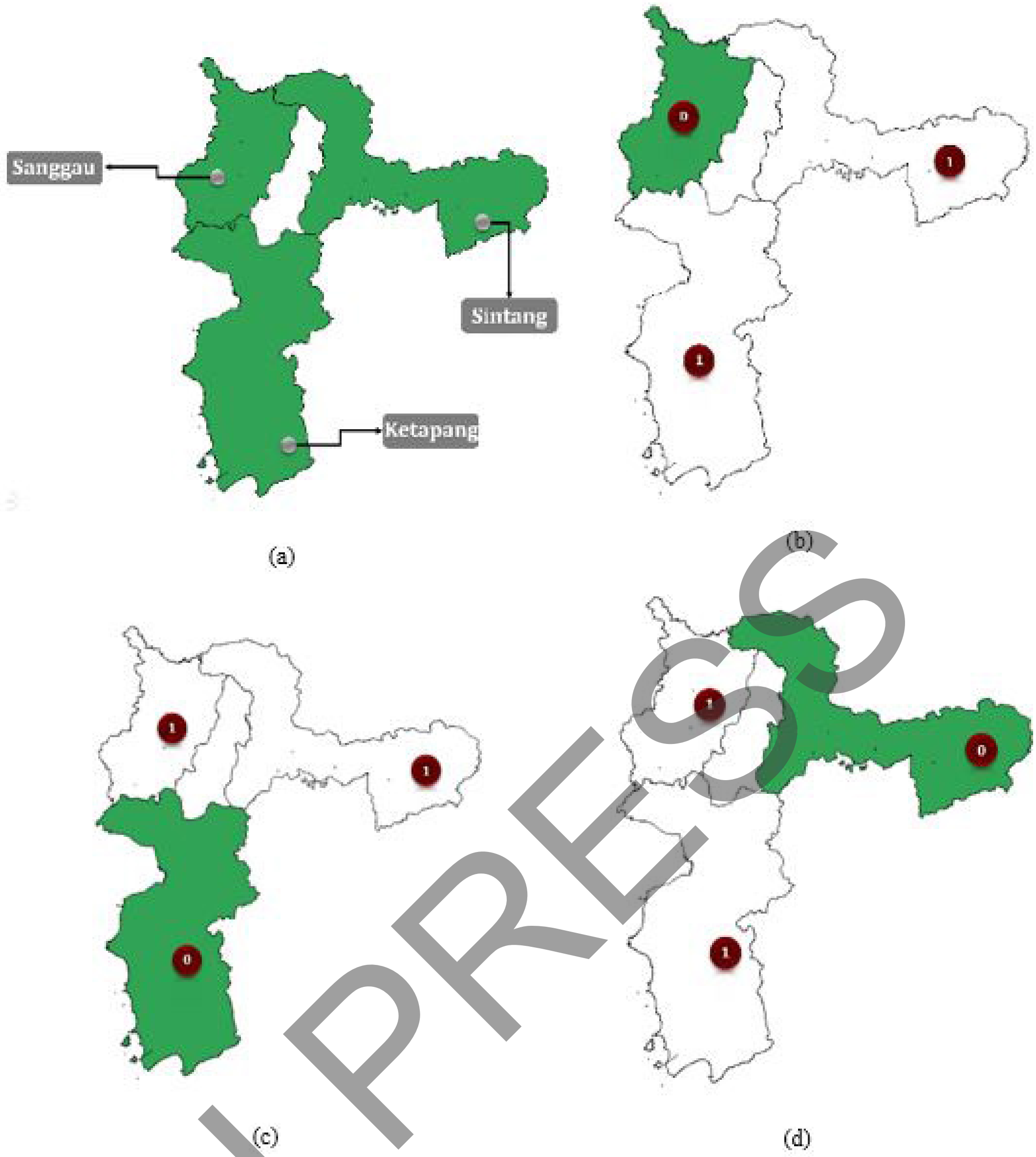


Figure 8 Queen Contiguity Map: (a) Location Objects (b) Sanggau (c) Ketapang (d) Sintang

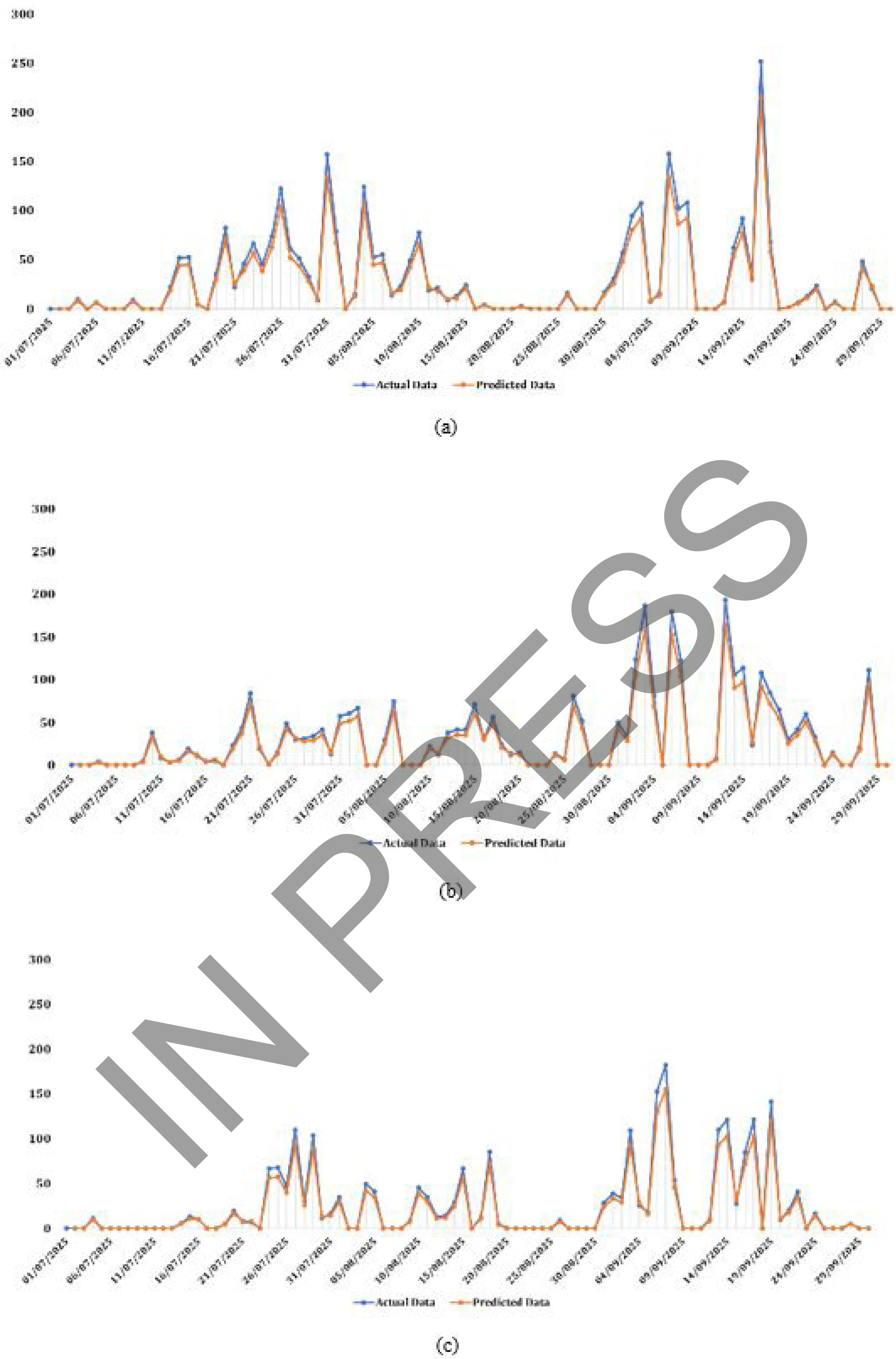


Figure 9 Comparison of Actual and Predicted Values in Regencies of West Kalimantan:
(a) Sanggau (b) Ketapang (c) Sintang