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## Comparison of GWANN and GWNBR in the Analysis of Positive Covid-19 Factors

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### ABSTRACT

Covid-19 emerged with a rapid transmission rate, yet the precise factors contributing to its spread were initially unclear. To reduce the number of positive Covid-19 cases in East Java, spatial analysis is essential for examining these influencing factors. This study employs local research approaches, utilizing adaptive bisquare kernel weights. The local research, where the estimated value differs by region, is carried out using the Geographically Weighted Negative Binomial Regression (GWNBR) and the Geographically Weighted Artificial Neural Network (GWANN) method. This research aims to compare the GWANN, and GWNBR methods to determine the more effective approach for analyzing Covid-19 factors in East Java. The best model is selected based on the  $R^2$  and RMSE values. The findings indicate that the Geographically Weighted Negative Binomial Regression (GWNBR) method is the more effective model, with an RMSE of 936.2055 and an  $R^2$  of 0.902, and subsequent clustering based on significant local coefficients produced four regional groups; notably, comorbidity prevalence was significant in all areas, while other determinants differed by locality. These findings indicate that accounting jointly for overdispersion and spatially varying relationships improves inference on Covid-19 case patterns and highlights comorbidity burden as a province-wide priority for intervention.

**Keywords:** Covid-19; GWANN; GWNBR; Overdispersion; Spatial Heterogeneity

### 1. Introduction

Covid-19 is a highly infectious virus posing a significant global challenge. It was initially identified in Wuhan City, China, though its origin remains unclear, and the number of cases continues to rise daily [10]. On January 30, 2020, the World Health Organization classified the 2019-2020 coronavirus outbreak as an International Public Health Emergency (PHEIC). The outbreak was later designated a pandemic on March 11, 2020. This disease, caused by the SARS-CoV-2 virus, is referred to as Coronavirus Disease 2019 [20]. In response, the Indonesian government has implemented various strategies to curb the spread of Covid-19, including establishing the Task Force for the

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Acceleration of Handling Covid-19. Additionally, the government has enforced Large-Scale Social Restrictions in several East Java cities, such as Surabaya, Sidoarjo, Malang, and Gresik. The aim of these restrictions is to reduce transmission by flattening the curve [19].

Java Island serves as the focal point for the Covid-19 outbreak in Indonesia. The majority of Covid-19 cases are concentrated on Java Island, specifically in DKI Jakarta (22.7%), East Java (19.3%), Central Java (8%), and West Java (6.3%). This information suggests that East Java Province is considered a region with a high number of positive Covid-19 cases [21]. To reduce the number of positive cases in East Java, it is crucial to identify the factors that could potentially contribute to an increase in cases. Each factor will have varying impacts across different regions due to the distinct social, economic, and cultural conditions present in each area. Therefore, spatial analysis is essential to assess the influence of these factors on each district or city within East Java.

Numerous prior studies have employed the Geographically Weighted Negative Binomial Regression (GWNBR) technique. The research about spatial distribution of delivery motorcycle crashes and related factors [13], finds that the GWNBR model outperformed the GLM in terms of AIC and RMSE values. A study on geographically weighted artificial neural networks [6] demonstrates that GWANN can achieve superior predictive performance compared to GWR, particularly when dealing with nonlinear data and high spatial variance. Research on Negative Binomial Regression [3] reveals the Poisson regression model exhibited an overdispersion issue, and based on the AIC value, the negative binomial regression model was identified as the most suitable model.

This research employs the methods that consider spatial (local) data effects. To analyze spatial factors, the study utilizes Geographically Weighted Artificial Neural Network (GWANN) and Geographically Weighted Negative Binomial Regression (GWNBR). GWANN integrates geographic weighting with artificial neural networks. An adaptive bisquare kernel weighting is used in this study. These two approaches aim to identify the optimal model for analyzing factors influencing the number of positive Covid-19 cases in East Java. The best model is determined using the value of  $R^2$  and RMSE. This research is expected to offer insights into the significant factors affecting the number of positive Covid-19 cases and serve as a reference for future studies.

## 2. Theoretical Framework

### 2.1. Poisson Regression

Poisson regression is a nonlinear regression model that is often used to model count data by looking at the number of events that occur in a certain time period or region [2,12]. Poisson regression has assumptions that must be met, namely the average value must be equal to the variance value (equidispersion). However, the condition that often occurs is that the variance is greater than the average value or is called overdispersion [8].

### 2.2. Negative Binomial Regression

Overdispersion is an assumption deviation that often occurs in Poisson regression. Overdispersion is a condition where the response variable data shows a variance greater than the mean value [14]. The Negative Binomial regression model serves as an alternative to Poisson regression in cases of overdispersion [4]. Negative Binomial Regression assumes that the response variable has a negative binomial distribution resulting from a mixed Poisson-Gamma distribution [11]. Negative Binomial distribution with parameters  $\mu$  and  $k$ , the mean value and its variance are as follows:

$$E(Y)=\mu \text{ and } V(Y)=\mu+a\mu^2 \quad (1)$$

According to Cameron dan Triverdi, 1998 [4], the probability function of a random variable Y with a negative binomial distribution is as follows:

$$f(y)=\frac{\Gamma(y+a^{-1})}{\Gamma(y+1)\Gamma(a^{-1})}\left(\frac{\mu}{a^{-1}+\mu}\right)^y\left(\frac{a^{-1}}{a^{-1}+\mu}\right)^{a^{-1}} \quad (2)$$

The Negative Binomial regression model can be stated as follows.

$$\mu_i = \exp(\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_p x_{pi}) \quad (3)$$

### 2.3. Multicollinearity

A common approach to identifying multicollinearity involves the use of Variance Inflation Factors (VIF). When the VIF exceeds 10, it indicates the presence of multicollinearity. The VIF is defined as follows.

$$VIF_k = \frac{1}{1 - R_k^2} \quad (4)$$

where  $R_k^2$  is the coefficient of determination between one variable and other predictor variables [18].

### 2.4. Spatial Heterogeneity

The aim of the spatial heterogeneity test is to determine if each observation location possesses a distinct identity, leading to spatial variations in the resulting regression parameters [7]. The Breusch-Pagan test [1] can be employed to assess spatial heterogeneity. The hypothesis for the Breusch-Pagan test is as follows:

$$H_0 : \sigma_1^2 = \sigma_2^2 = \dots = \sigma_p^2 = \sigma^2 \text{ (the variance between locations is the same)}$$

$$H_1 : \text{there is at least one } \sigma_i^2 \neq \sigma^2 \text{ (variance between different locations)}$$

The Statistic:

$$BP = \left(\frac{1}{2}\right) f^T Z (Z^T Z)^{-1} Z^T f \sim X^2_{(p)} \quad (5)$$

$H_0$  is rejected if the test statistic  $BP > X^2_{(p,\alpha)}$  or  $p\text{-value} < \alpha$ , which means that the variance between locations is different.

### 2.5. GWNBR Modeling

Before building a GWNBR model, it is necessary to calculate bandwidth and spatial weighting. The method used in determining the optimum Bandwidth is the CV (Cross Validation) method with the following equation [5].

$$CV(h) = \sum_{i=1}^n (y_i - \hat{y}_{\neq i}(h))^2 \quad (6)$$

With  $\hat{y}_{\neq i}$  is the estimator value  $y_i$  where is the observation location  $(u_i, v_i)$  which are not included in the assessment process [16]

Spatial weighting is required in the GWNBR assessment at a point  $(u_i, v_i)$ . The weight used is the adaptive bisquare kernel with the following formulation [15].

$$w_j(u_i, v_i) = \begin{cases} \left(1 - \left(\frac{d_{ij}}{h_i}\right)^2\right)^2, & \text{for } d_{ij} \leq h_i \\ 0, & \text{for } d_{ij} > h_i \end{cases} \quad (7)$$

where  $d_{ij}$  is Euclidean distance between locations  $(u_i, v_i)$  to location  $(u_j, v_j)$  and  $h_i$  is the adaptive bandwidth value [17].

The GWNBR model generates local parameters with each location having different parameters [9]. The GWNBR model is formulated as follows:

$$y_j \sim NB \left[ t_j \exp \left( \sum_k \beta_k(u_j, v_j) x_{jk} \right), \theta(u_j, v_j) \right]; j=1, \dots, n \quad (8)$$

## 2.6. GWANN Modeling

Geographically Weighted Artificial Neural Network (GWANN) is a variant of ANN that combines geographic weights from connection weights. The basic ANN consists of input, hidden, and output layers. The basic ANN connection weights from the hidden layer to the output can be interpreted as the linear model coefficients of the nonlinearly transformed variables, namely the output of the hidden neurons. Thus, when the connection weights between the hidden and output layers are estimated by utilizing the geo-weighted error function, this can be interpreted as a GWR model. The construction of the GWANN model is identical to the basic ANN, except that each GWANN hidden neuron is assigned to a location in geographic space [6].

## 3. Methods

This study uses secondary data sourced from the publication of health profile data at the 2020 East Java Provincial Health Office and the official website of the Central Statistics Agency (BPS) of East Java Province with 38 locations, the regencies/cities in East Java Province. In this study, the dependent variable was used, namely the number of positive cases of Covid-19 in East Java ( $Y$ ). The study's independent variables include the hospital's service performance indicator ( $X_1$ ), the proportion of elderly individuals ( $X_2$ ), the percentage of impoverished people ( $X_3$ ), the rate of adequate sanitation ( $X_4$ ), and the percentage of patients with comorbid conditions such as hypertension and diabetes mellitus ( $X_5$ ).

The analysis begins with descriptive statistical analysis to examine the characteristics of the variables using measures such as the mean, variance, minimum, and maximum values. A multicollinearity between independent variables is then conducted using the Variance Inflation Factor (VIF) to ensure that the independent variables are not highly correlated. Next, an overdispersion is performed to determine whether the variance of the response variable exceeds its mean. If overdispersion occurs, Negative Binomial Regression (NBR) is used as the appropriate modeling approach for count data. In addition, a spatial heterogeneity test is carried out to identify whether relationships between variables differ across locations.

After confirming spatial heterogeneity, spatial modeling methods are applied. The first method is Geographically Weighted Artificial Neural Network (GWANN), which includes defining the data in matrix form, calculating Euclidean distances between locations, performing hyperparameter tuning, and selecting the best GWANN model. The second method is Geographically Weighted Negative Binomial Regression (GWNBR), which involves selecting the optimal bandwidth, determining spatial weights, and estimating the GWNBR model. Finally, the performance of the GWANN and GWNBR models is compared using Root Mean Square Error (RMSE) and the coefficient of determination ( $R^2$ ) to determine the best model.

## 4. Results and Discussion

This is a statistical analysis that describes each variable. From this examination, we observe that the variance in the number of Covid-19 positive cases exceeds the mean, suggesting that the data exhibits overdispersion.

**Table 1.** Descriptive Statistical Analysis

Variable	Mean	Variance	Minimum	Maximum
Y	2214	9180541	390	18164
$X_1$	3.421	1.061166	1	8
$X_2$	13.85	9.466327	8.19	20.31

Variable	Mean	Variance	Minimum	Maximum
$X_3$	11.021	20.86483	3.89	22.78
$X_4$	94.35	65.32959	69.9	100
$X_5$	2.6316	2.801435	0.3467	6.8927

The subsequent action involves conducting a multicollinearity assessment by utilizing the Variance Inflation Factor (VIF) value. A VIF value exceeding 10 suggests the existence of multicollinearity among the independent variables. Based on the VIF value, all variables demonstrate an absence of multicollinearity.

**Table 2.** VIF Value

Predictor	VIF
$X_1$	1.133080
$X_2$	1.083544
$X_3$	1.143565
$X_4$	1.144212
$X_5$	1.092557

The spatial heterogeneity test is conducted to assess the variation in regional relationships. One method employed for this purpose is the Breusch Pagan test. The results of the tests indicated a p-value of 0.0162. With a significance level of 0.05, the decision was made to reject, indicating the presence of spatial heterogeneity in the data under observation. The subsequent step involves constructing model using the GWNBR and GWANN methods.

#### 4.1. GWNBR Modelling

Using adaptive bisquare kernel to find optimum bandwidth and weight, we construct the GWNBR model. Here is the parameters of the GWNBR model using Jember Regency as an example.

**Table 3.** GWNBR Model Parameter Testing in Jember Regency

Parameter	Coefficient	Z-value	p-value
(Intercept)	9.538047	6.837047	8.084223e-12
$X_1$	-0.176467646	-1.75685748	0.07894210
$X_2$	-0.08177175	-1.678473	0.093254845
$X_3$	-0.03400112	-1.216770	0.22369167
$X_4$	-0.007375483	-0.6359590	0.5248031
$X_5$	0.3096518	5.780492	$7.448252 \times 10^{-9}$

The *p-value* in Table 3 is compared to the  $\alpha$  value of 0.025 and the p-value of variable that is less than 0.025 is the  $X_5$  variable, this shows that the variable proportion of comorbid sufferers has a significant effect on the positive number of Covid-19 in East Java. Adjustments to the GWNBR model in Jember Regency are as follows.

$$\mu = \exp(9.538047 + 0.3096518x_5)$$

Based on the GWNBR model in Jember Regency, it can be seen that service performance indicators in hospitals, the percentage of the elderly population, the percentage of poor people and the percentage of proper sanitation have not significant effect on the number of positive cases of Covid-19 in Jember. Meanwhile, the percentage of comorbid sufferers has a positive effect on the number of positive cases of Covid-19 in Jember, means that a large number of comorbid sufferers in Jember correlates with a large number of positive cases of Covid-19 as well, and vice versa.

#### 4.2. GWANN Modelling

GWANN modeling is a combination of spatial weighting and ANN weighting. GWANN modeling for the number of positive cases of Covid-19 in East Java uses the adaptive bisquare kernel function with a predefined learning rate of 0.01 with the SGD optimizer. The activation function used

in GWANN is the hyperbolic tangent. In GWANN, a single hidden layer is used with 10-300 hidden neurons. The search for the appropriate bandwidth value was determined using the Golden Section approach and in this study different batch sizes were used, namely 11, 32, 64, and 128. Based on the predetermined parameters, 52 models were obtained and one best model was obtained by looking at the smallest RMSE value, the number of iterations and the time needed to run the program. The value of the smallest RMSE, namely 1680.92, is located in a batch size of 128, hidden neurons of 250 and the time used is 86.7 seconds. GWANN modeling also gives the variable importance. The variable importance is used to determine the level of the variable that has a major influence on the number of positive cases of Covid-19 in East Java. The greater the value of the variable importance, the greater the effect on the number of Covid-19 cases in East Java. The following is the variables that have highest variable importance value of each regency/city.

**Table 4.** The Variables with Highest Importance Value of Each Regencies/Cities

Importance Variable	Regency/City
$X_1$	Kediri, Lumajang, Jember, Magetan, Sumenep, City of Mojokerto
$X_2$	Ponorogo, Trenggalek, Tulungagung, Blitar, Nganjuk, Madiun, Tuban, Pamekasan, City of Kediri, City of Blitar, City of Madiun, City of Surabaya
$X_3$	Pacitan, Malang, Banyuwangi, Sidoarjo, Jombang, Ngawi, Bojonegoro, Gresik, City of Malang, City of Probolinggo, City of Pasuruan
$X_4$	Bondowoso, Situbondo, Probolinggo, Pasuruan, Mojokerto, Lamongan, Bangkalan, Sampang, Batu

Table 4 describe the regencies/cities that have same highest importance variable. There are four group of regencies/cities based on the highest value of variable importance. The most importance variable in Kediri, Lumajang, Jember, Magetan, Sumenep, City of Mojokerto is hospital's service performance indicator ( $X_1$ ). This means that in those areas the service performance indicator at the hospital is most correlated to the number of positive cases of Covid-19 compared to other independent variables.

#### 4.3. Best Model Selection

Selection of the best model is based on two values, namely the RMSE and value  $R^2$ . A good model have a small RMSE value and a large  $R^2$  value.

**Table 5.** The RMSE and  $R^2$  value

Method	RMSE	$R^2$
GWNBR	936.2055	0.9019481
GWANN	1604.93	0.7118453

Table 5 shows that the GWNBR produces smaller RMSE values than GWANN model. The  $R^2$  value generated from the GWNBR is also greater than GWANN model. It can be concluded that the GWNBR model is a better model for modeling the factors that influence the number of positive cases of Covid-19 for each regency/city in East Java in 2020.

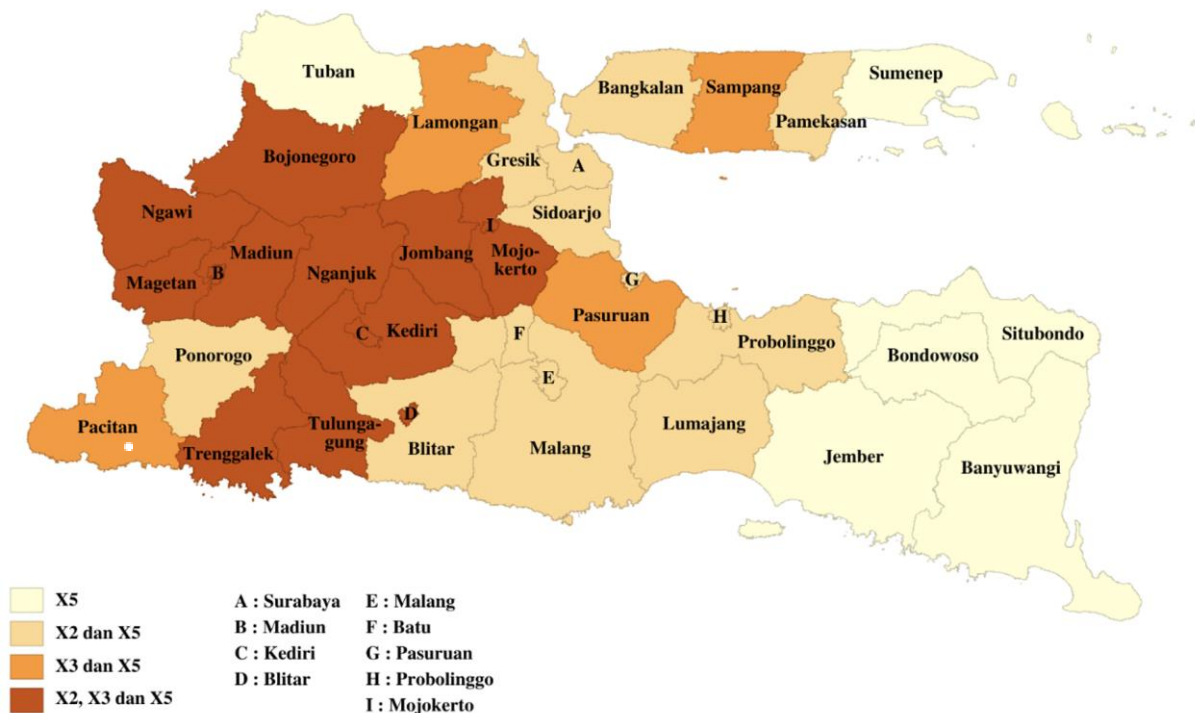
#### 4.4. Grouping Locations Based on The Best Model

Since the GWNBR model is considered the most effective, clustering is conducted using this model. For clustering, a significance test of the GWNBR model's parameters is performed. The purpose of testing the GWNBR parameter estimates is to identify which variables impact the number of Covid-19 positive cases in each regency or city in East Java. The calculations reveal that the value of  $|Z_h|$  varies by location. Parameters of the model are deemed significant if  $|Z_h| > 1.96$  using a significance level of 5%. Below is a grouping of locations based on the significant variables.

**Table 6.** Grouping Locations Based on Significant Variables

Significant Variables	Regency/City
$X_5$	Jember, Banyuwangi, Bondowoso, Situbondo, Tuban, Sumenep
$X_2$ and $X_5$	Ponorogo, Blitar, Malang, Lumajang, Probolinggo, Sidoarjo, Gresik, Bangkalan, Pamekasan, City of Malang, City of Probolinggo, City of Pasuruan, City of Surabaya, City of Batu
$X_3$ and $X_5$	Pacitan, Pasuruan, Lamongan, Sampang,
$X_2, X_3$ and $X_5$	Trenggalek, Tulungagung, Kediri, Mojokerto, Jombang, Nganjuk, Madiun Magetan, Ngawi, Bojonegoro, City of Kediri, City of Blitar, City of Mojokerto, City of Madiun

The locations are categorized into four distinct groups, each defined by significant variables. Despite these differences, the rate of patients with comorbidities such as hypertension and diabetes mellitus ( $X_5$ ) remains significant across all areas. The arrangement of districts and cities in East Java Province, based on these significant variables, is depicted in the following figure.



**Figure 1.** Grouping of Regencies/Cities Based on Significant Variables

**5. Conclusion**

Based on the RMSE and  $R^2$  findings, the GWNBR model proves to be the most efficient in forecasting the number of Covid-19 positive cases. This model, which employs the adaptive bisquare kernel weighting function, categorizes regions into four distinct groups according to various significant factors. The variable indicating the rate of patients with comorbidities ( $X_5$ ) is important in all regions. The regions of Jember, Banyuwangi, Bondowoso, Situbondo, Tuban, and Sumenep are characterized by the  $X_5$  variable, while Pacitan, Pasuruan, Lamongan, and Sampang are defined by the  $X_3$  and  $X_5$  variables. Other

areas are grouped based on the  $X_2, X_5$  and  $X_2, X_3, X_5$  variables. This study highlights that accounting simultaneously for overdispersion and spatially varying relationships is crucial for understanding Covid-19 case patterns in East Java and underscores the comorbidity burden as a key province-wide factor, with other determinants varying by locality.

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