International Journal of Science and Research (IJSR)
ISSN (Online): 2319-7064
Index Copernicus Value (2015): 78.96 | Impact Factor (2015): 6.391

Relation between Air Cargo Transported and Airport Characteristics in Indonesia using Geographically Weighted Regression

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Abstract: ***Air cargo shipments in Indonesia have recently increased. This research aims to analyze spatial inequality on the relation of air cargo volume which is transported and airport characteristics in Indonesia. The characteristics of the airport that examined are the length of airport runway and the number of departures of the aircraft. We use data of 102 airports in Indonesia. A geographically weighted regression (GWR) model has been fitted to analyze the spatial heterogeneity. The GWR model obtained is compared with the global regression model using some comparative statistics. The modeling results show that the number of air cargo transported correlates with the length of the airport runway and its relationship varies across the airports. The influence of the runway length on air cargo transportation is higher at airports in western Indonesia, while less influence occurs on airports in eastern Indonesia. The number of air cargo is also positively correlated with the number of departures of the aircraft, which influence the number of departures aircraft at airports on the island of Sumatra which is higher than in other airports in Indonesia.***

Keywords: geographically weighted regression, air cargo, airport characteristic, spatial variation

1. Introduction

Indonesia as a vast archipelagic country with a large population, is faced with a tough challenges in the transportation sector. Air transport has an important role especially when associated with the need for inter-regional transport with short travel times. One of these air transport activity products is cargo transportation. During 2011–2015, domestic cargo transportation in Indonesia has increased 6.57% per year [1]. The comprehension of the factors related to air cargo transportation is necessary to expedite the distribution of goods to all regions in a fast time.

Several studies of factors related to cargo transport volume had been conducted. Zhang [2] had shown the relation of air cargo with the trade growth and the per capita of gross domestic product (GDP). Furthermore, Kasarda and Green [3] stated that air cargo was a leading indicator of trade and GDP growth. Chang and Chang [4] had also shown a relation between economic growth and air cargo expansion. Yet there was an interesting finding from Yuan *et al*. [5] that improving airport land capacity utilization was positively correlated with the volume of air cargo in Singapore, while in Hong Kong both variables were negatively correlated. Likewise, the high labor costs in Hong Kong were negatively correlated with the volume of air cargo, while in Singapore the two variables were not correlated. These findings will be easily understood when examined in a spatial-based research. In this type of research, the findings in one area may be different from those in other areas.

Spatial-based research is feasible to be used to evaluate the relation of air cargo volumes that transported to the airport characteristics in Indonesia. This is because the airport infrastructure in Indonesia is not the same. Based on its hierarchy, there are four types of airports in Indonesia, namely the spoke airport, the hub airport with the scale of services are primary, secondary, and tertiary. The activities of the airports are intertwined with each other. In addition, there are some areas that can only be reached by air transport, so the airports in some area have a function as an opener of isolated area. Based on these considerations, we hypothesized that the relation of the number of air cargo that transported to the characteristics of airports was spatially non-stationary.

One of the relatively new methods for analyzing spatial relations among variables is the geographically weighted regression (GWR) method. This statistical method expands the traditional regression model framework into a local regression model that allows different estimation of regression parameters at each point of the study site [6]. The relationship between the dependent variable (Y) and the independent variable (X) in the GWR model is not the same across all locations [7]. The GWR method has been used to analyze the public health issues [8], resource management [9], the environment [10], and so on.

The main objective of this study was to evaluate the spatial heterogeneity of the relationship between the volume of air cargo transported to the characteristics of airports in Indonesia with the GWR model. In this case, the characteristics of the airport that investigated were the length of the runway and the total departure of the aircraft. The GWR model obtained was compared with the global regression model using some statistical test. The results of this study were beneficial to the parties involved in the policy program relating to the reduction of the cost of distribution of goods to all regions of the country.

2. Materials and Methods

2.1. Study Area

Indonesia is an archipelagic country located between 6°04'30" north latitude and 11°00'36" south latitude and between 94°58'21" to 141°01'10" east longitude [11]. Indonesia consists of 34 provinces. Each province has one or more airports, both domestic and international airports. The airport is an area of land and/or water with certain limits used as a place for landing and take-off aircraft, passengers, loading and unloading of goods, and intra and intermodal shifts, equipped with aviation safety and security facilities, as well as basic facilities and other supporting facilities.

2.2. Data Collection

Data for amount of transported cargo (kg) every airport during 2015 was booked from Statistics Indonesia [1]. One airport was defined as one spatial unit. The coordinates of the airport location were taken from the Ministry of Transportation [12]. The number of transported cargo was chosen as dependent variable (Y) in the regression modeling.

The characteristics of the airport, in this study were the runway length (X_1) and the number of flight departures (X_2), used as independent variables. The number of aircraft departure data was obtained from Statistics Indonesia [1]. Meanwhile, the runway length data (m) was taken from hubud.dephub.go.id. The number of data for each variable was n = 102.

2.3. Statistical Methods

Since independent variables have different scales of measurement, variables were standardized according to:

$$X_{ik}^{*} = (X_{ik} - \bar{X}_k)/s_k \quad (i = 1,2,\cdots,n;\ k = 1;2) \tag{1}$$

where X_{ik}^{*} is the value of the standardized variable at airport position i, X_{ik} is the original data, $\bar{X}_k$ is the mean of the corresponding variable, and s_k is the standard deviation.

A multiple linear regression model was initially formed using ordinary least squares (OLS) method to analyze the global relationship between the volume of cargo transported (Y) and the independent variables (X). This global regression model assumes that the relationship between variable Y and variable X is spatially stationary. This regression model is expressed by:

$$Y_i = \beta_0 + \beta_1 X_{i1}^{*} + \beta_2 X_{i2}^{*} + \varepsilon_i \tag{2}$$

where Y_i is the amount of cargo transported at the airport i ($i = 1,2,\cdots,102$); X_{i1}^{*} is the runway length at the airport i; X_{i2}^{*} is the number of flight departures at the airport i; β_0 is the intercept coefficient; β_1 and β_2 are the OLS regression coefficients; ε_i is the error that is assumed to be distributed $N(0,\sigma^2)$.

As in the regression modeling, an early diagnosis was initially performed to test for an autocorrelation error using Durbin-Watson (d) statistics. If the d value obtained is greater than the upper bound d_U then the autocorrelation does not occur in the model error [13]. The significance of global regression is represented by t statistics, error sum of squares (ESS), Akaike information criterion (AIC), and adjusted coefficient of determination R^2 [13].

The spatial variation of the relation of air cargo transported (Y) to length of runway (X_1) and total aircraft departure (X_2) analyzed with GWR model. Unlike the tradisional regression, GWR model allows the estimation of regression parameters at different airports [6]. The GWR model used was:

$$Y_i = \beta_0(u_i,v_i) + \beta_1(u_i,v_i)X_{i1}^{*} + \beta_2(u_i,v_i)X_{i2}^{*} + \varepsilon_i \tag{3}$$

where $\beta_0(u_i,v_i)$, $\beta_1(u_i,v_i)$, and $\beta_2(u_i,v_i)$ are the GWR coefficients at the airport i; the location point of the airport i expressed by latitude and longitude coordinates (u_i,v_i); and ε_i is the error that is assumed to be distributed normal.

The early stage of GWR modeling is the determination of the latitude and longitude coordinates of each airport. The geographic coordinates are used to determine the Euclidean distance between the airport i and the airport j:

$$d_{i;j} = \sqrt{(u_i - u_j)^2 + (v_i - v_j)^2}\,. \tag{4}$$

The distance size in Equation (4) serves as the basis for weighting the data in estimating GWR parameters. The closer the distance to the airport that its parameter were estimated, the greater the weight of the data in the estimated parameters. In this study, data weighting was done by using the Gauss function:

$$\psi_{i(j)} = \exp\left(-d_{i;j}^2 / 2b^2\right) \tag{5}$$

with $b > 0$ is the bandwidth constant. This constant was determined by the value of cross-validation (CV), by determining the value b that minimized:

$$\mathrm{CV}(b) = \sum_{i=1}^{m}\left(Y_i - \hat{Y}_{\neq i}(b)\right)^2 \tag{6}$$

where Y_i is the observed value of the dependent variable at the airport i and $\hat{Y}_{\neq i}(b)$ is the estimated value of Y_i based on the GWR model obtained by using values that do not include in the airport observations i [6]. This optimum b value is obtained iteratively by taking a small b initiation value.

The Gauss function in Equation (5) was an exponential function that gives the weight of 1 at the airport that the parameter was estimated and the monotonous weight drops at the other airport data as the distance between airports increases. The airport that close to the point where the parameter of the airport was estimated, has a greater impact than the distant airport. The weighted function of Gauss is used in the formation of a weighted matrix:

$$\mathbf{W}(u_i,v_i) = \mathrm{diag}\left(\psi_{i(1)},\psi_{i(2)},\cdots,\psi_{i(102)}\right) \tag{7}$$

where $0 \le \psi_{i(j)} \le 1$ is the weight of airport data j for parameter estimation at airport i. Each airport data has one weighted matrix $\mathbf{W}(u_i,v_i)$ in estimating the parameters of the observation. With the approach of matrix algebra, estimation of parameter $\hat{\underset{\sim}{\beta}}(u_i,v_i) = \left(\hat{\beta}_0(u_i,v_i),\hat{\beta}_1(u_i,v_i),\hat{\beta}_2(u_i,v_i)\right)^T$ in the airport i with weighted least squares (WLS) method is represented as [6]:

$$\hat{\beta}(u_i,v_i)=\left[\mathbf{X}^T\mathbf{W}(u_i,v_i)\mathbf{X}\right]^{-1}\mathbf{X}^T\mathbf{W}(u_i,v_i)\underset{\sim}{\mathrm{Y}}\ . \quad (8)$$

GWR modeling was calibrated on the transformed data. Diagnosis was first performed to test autocorrelation error with Durbin-Watson statistics.

The significance test of GWR model was done by hypothetical test suggested by Brunsdon *et al*. [14]. The null hypothesis in this test states the function of $\beta_k(u,v)$ which is constant in all points (u,v) in the research area for $k=0,1,2$. If there is no evidence to reject null hypothesis, the global regression is sufficient to describe this research data. Meanwhile, testing the variation significance of each parameter β_k along the location will be done $F_3(k)$ statistic which recommended by Leung *et al*. [7]. The significance of GWR model is also expressed by error sum of squares (*ESS*) and the coefficient of determination R^2. Benchmarking the GWR model with the OLS global regression model will be done with Akaike information criterion (*AIC*) statistics. Based on this criterion, regression model that has the smallest *AIC* value is the best model [6].

3. Results and Discussion

Estimating an OLS model in the form of Equation (2) gives the result:

$$Y=-1105712+654X_1+239.7X_2 \quad (9)$$

where Y is the amount of transported cargo, X_1 is lenght of runway, and X_2 is total aircraft departure. This model is globally appropriate for all airports. This is a global regression model that does not assume spatial non-stationary of parameters. Evaluation of the error of this model shows that the Durbin-Watson statistic d = 1.886 where the value is greater than the upper limit d_U = 1.72 (α = 0.05). This shows that there is no autocorrelation in the model error. All *P*-values associated with the regression coefficients in the model less than 0.05 (Table 1). Hence, airport characteristics affect the amount of cargo loaded in Indonesia. The value of the variance inflation factor (VIF) = 1.77 for each variable less than 10 indicates that the independent variables used are not correlated.

Table 1: Estimated coefficients of OLS regression

Variable	$\hat{\beta}$	*SE*	*t*	*P-value*	*VIF*
Constant	-1105712	320778	-3.45	0.001	
X_1	654	192	3.40	0.001	1.77
X_2	239.7	22.9	10.47	0.000	1.77

SE : standard error

The model has $ESS=8.34\times10^{13}$, $AIC=3090.33$, and the adjusted $R^2=74.52\%$. Diagnosis of the model also indicates that the error is close to the normal distribution.

Based on cross-validation criteria, GWR modeling of the data gives the optimum bandwidth value of b = 7.543. Thus, the weighted function of Gauss used is:

$$\psi_{i(j)}=\exp\left(-d_{i;j}^2/7.543\right). \quad (10)$$

Table 2 presents a summary of parameter estimates (regression coefficients) of the obtained GWR model. All global regression coefficient values are in the interval of regression coefficient value of GWR model.

Table 2: Estimated GWR model coefficients

Coefficient	*Minimum*	*Median*	*Maximum*	*Global*
$\hat{\beta}_0$	-2020802	-979160	-111037	-1105712
$\hat{\beta}_1$	11	555	1191	654
$\hat{\beta}_2$	185.8	236.2	419.9	239.7

The diagnosis of the GWR model error provides the Durbin-Watson d = 1.968 statistic whose the value is greater than the upper bound d_U = 1.72 (α = 0.05). This indicates that autocorrelation does not occur in the error of this model. Diagnosis of the model also indicates that the error approaches normal distribution.

GWR modeling results provide a error sum of squares of $ESS=5.50\times10^{13}$ which is smaller than the global regression model. This shows that the GWR model yields estimates $\hat{Y}$ closer to the value of Y than global regression models. The coefficient of determination of the GWR model (R^2 = 83.54%) also increases from the OLS regression model. Table 3 provides a summary of the calculation of the F statistic used to test the significance of the GWR models. *P*-value is smaller than 0.05 indicates that the GWR model is more significant than the global regression model.

Table 3: Comparison between GWR and global regression

Source of variation	*ESS*	*MS*	*F*	*P-value*
OLS error	8.34×10^{13}			
GWR improvement	2.84×10^{13}	3.49×10^{12}		
GWR error	5.50×10^{13}	6.05×10^{11}	5.774	0.000

MS (mean square)

The value of Akaike information criterion obtained from the GWR model is $AIC=3053.22$. This value is smaller than that produced by global regression models. This indicates that the GWR model is more feasible to use to describe this research data than the global model. Subsequent tests showed that the coefficients $\hat{\beta}_0,\hat{\beta}_1,\hat{\beta}_2$ significantly varying at each airport (see Table 4). This can be seen from *P*-value relating to the GWR coefficient which is smaller than 0.05.

Table 4: Nonstationarity of parameters in GWR model

Coefficient	*Numerator d.f.*	*Denominator d.f.*	$F_3(k)$	*P-value*
$\hat{\beta}_0$	32.507	94.325	4.514	0.000
$\hat{\beta}_1$	26.719	94.325	4.392	0.000
$\hat{\beta}_2$	22.503	94.325	6.323	0.000

d.f. (degree of freedom)

This study shows that the total of transported cargo is related to the length of runway and number of aircraft departures. The longer the runway of the airport, the greater the possibility that the airport will be landed by large planes. The large aircraft can load much freight compared to the small aircraft. Likewise, the more airplane departures, the greater the space for cargo transported.

These results reinforce the findings of Yuan *et al.* [5] in Hong Kong and Singapore that air side capacity utilization shows a very strong relationship with air cargo volume. Likewise, Jarach [15] highlighted that a business must integrate the infrastructure of the airport into the supply chain of raw materials.

GWR modeling provides further indication that the relationship between the amounts of cargo transported to the length of runway in Indonesia is spatially variable. This means that at some airports the runway length contributes significantly to the total of transported cargo, while at other airports the length of the runway contributes moderately or lowly to the total increase of transported cargo. Based on regional grouping, the effect of runway length on total of transported cargo is greater at airports in southern parts of Sumatra, Java, and Bali, moderate influence on airports in the northern parts of Sumatra, Kalimantan, Sulawesi and Nusa Tenggara, while smaller effect occur on airports in Maluku and Papua.

The GWR modeling also states that the air cargo volume relationship with the number of departure aircraft is spatially non-stationary. The volume of air cargo transported at airports in northern Sumatra is heavily influenced by the number of departures. Meanwhile, moderate effects occur on the volume of air cargo transported at airports in the southern part of Sumatra, whereas in most of the airports in Indonesia other than Sumatra gets little effect.

4. Conclusion

The volume of air cargo transported is positively correlated with the length of the airport runway and the number of departures in Indonesia. The relation of the volume of air cargo that is transported to the characteristics of the airport is varied at each airport.

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