Accessibility model of BRT stop locations using Geographically Weighted regression (GWR): A case study in Banjarmasin, Indonesia

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Accessibility model of BRT stop locations using Geographically Weighted regression (GWR): A case study in Banjarmasin, Indonesia

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ABSTRACT

Bus Rapid Transit (BRT) has advantages over rail-based systems as a public transportation system. The ease of implementation and low investment costs attract many cities to develop BRT systems, including Banjarmasin, Indonesia. Banjarmasin currently has eight BRT stop points that reach only two sub-districts out of five. The limited range of BRT stops within the city can affect the level of accessibility of the BRT system. The accessibility of the transit system itself can be seen from the number of daily passengers. This study aims to analyze the criteria that affect the level of accessibility of the BRT stops in the study area and then compile a model based on significant criteria. Previous literature on accessibility modeling shows varied methods and approaches. In this study, the system accessibility was measured using the composite method and modeled using Geographically Weighted Regression (GWR), which is a relatively new approach. The results show that seven criteria affect the level of accessibility of the BRT stops. The model was first built mathematically using OLS. Then, GWR analysis was accomplished on spatial variables, resulting in a higher significance model. Furthermore, the GWR produces a visual-spatial model and performs simulation and sensitivity tests to make the research purpose more informative. The spatial criteria for the accessibility of the BRT stop locations in the model include the distance of stops to the road intersection, mix-use entropy index, population density, and land value.

Introduction

Accessibility plays an essential role in a public transportation system. There is awareness of big cities facing the problem of limited provision of transportation infrastructure. However, the demand growth for transportation is continuously increasing to infinity. Hence, cities were challenged to develop public transportation systems with high accessibility, including Mass Rapid Transit (MRT), Light Rail Transit (LRT), and Bus Rapid Transit (BRT). BRT has advantages in faster implementation, lower costs, and greater strategic effect than rail-based systems (ITDP-Indonesia, 2018).

The existence of public transportation in Banjarmasin such as the minibus taxi or "angkot" experienced a drastic decline both in terms of the number of passengers and fleet. Angkot in its operational service does not have a fixed stop. Their system

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is confusing because we can get on and get off whenever or wherever we want. To get in the angkot, we just need to stand at the roadside and wave our hands to the driver. Furthermore, private transportation has increased by 10 % yearly and is not proportional to road capacity growth. Existing public transportation only has a percentage of 3.12 % of the total traffic movement in Banjarmasin. One of the causes of this condition is that the existing public transportation conditions are uncomfortable and unattractive (Radam, 2018).

The ineffectiveness of the previous system has led to the Government's initiation to develop a BRT system with an advantage in lower cost and faster implementation. The Banjarbakula BRT system is planned to serve at a metropolitan scale across two cities and three districts. The operation of Banjarbakula BRT in Banjarmasin area currently serves Banjarmasin-Banjarbaru round trips with eights BRT stops within Banjarmasin. In terms of spatial distribution, the locations of BRT stops in Banjarmasin are only in the districts of East Banjarmasin and Central Banjarmasin. The BRT stops are not reached the activity centers in the northern, western, and southern parts of Banjarmasin.

Recognizing the BRT limitation, The Trans-Banjarmasin feeder under different management initiated to connect areas that the Banjarbakula BRT had not reached. However, this feeder uses the existing stop points belonging to the angkot. The problem is that the stop points belonging to angkot are already abandoned because users can get on and off whenever or wherever they want. There is a question about the accessibility of the angkot stop point that is not yet known, and no further study to integrate it into the BRT system.

For reference, the TransJakarta BRT system allows feeder buses to pick up passengers without stopping at designated stops and has many flexible routes. However, the area of activity centers is still supported by the trunk system of TransJakarta (Fitriati, 2010). In the case of TransMilenio Bogota, one of the accessibility criteria is travel time by walking to stops affects the quality of the BRT system, which can increase the value of an area in urban (Munoz-Raskin, 2010).

Based on the background above, the main problem is that the development of BRT systems in the study area has not yet considered accessibility a critical factor in the transit system. The re-use stop location of previous public transportation that in fact failed to attract users needs evaluation and further study of its accessibility. Two research questions can be formulated. First, what are the criteria that affected the accessibility of the BRT stop locations. Second, where is the BRT stop's location that meets the criteria of accessibility to develop in the study area. The research objectives are to know the criteria that affect the accessibility of the BRT stop location and develop models and simulations of BRT stop locations with high accessibility criteria in the study area. In the first section, the background and objectives of the research will be explained. The second section contains related literature references, and the third section will explain the methodology used. The fourth section describes the results and discussion, which closes with the conclusion in the fifth section. Furthermore, Geographically Weighted Regression (GWR) was expected to produce a more significant and informative model to answer the research questions.

Literature review

The measurement of transit accessibility

In public transportation, there is a definition of accessibility which includes the choice of modes. Transit accessibility is an accessibility approach that is more specific in measuring the level of accessibility of the urban transportation system, especially the public transportation system to the pedestrian system. Transit accessibility emphasizes the point of view of service users (transit users) in utilizing the existing transit system. These users generally have their own considerations of accessibility parameters that they think are in accordance with their wishes, such as travel time, number of transfers, costs/fares, etc. Transit accessibility modeling can be divided into system accessibility, system-facilitated accessibility, and integral accessibility (Malekzadeh and Chung, 2020). The illustrations can be seen in Fig. 1.

Systems accessibility deals with physical access to the public transit network, estimating how easy it is for a person to reach public transit stops using different travel modes or first-mile. Systems-facilitated accessibility measures a traveler's ability to reach an opportunity by incorporating the travel time or cost spent in the transit network. Integral accessibility

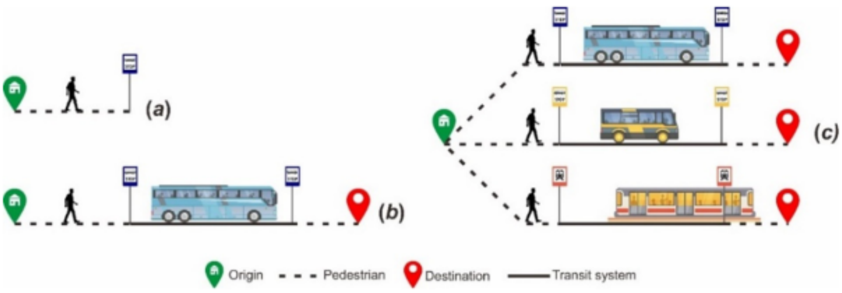

Fig. 1. (a) System accessibility, (b) system-facilitated accessibility, (c) integral accessibility.

is associated with measuring overall access to a number of possible destinations, revealing how easy it is for the resident to travel from an origin to opportunities using public transit (Lei and Church, 2010) and (Mavoa et al., 2012) as cited in (Malekzadeh and Chung, 2020). In this study, as the BRT system is in an earlier stage, the output model is optimized for planning the system accessibility. In planning a public transportation system, access to the transit system is one of the main factors as important as the quality of the transit system (Mavoa et al., 2012).

There are challenges in developing transit accessibility models, and a review of previous studies from (Malekzadeh and Chung, 2020) shows varied methods and approaches. In terms of measurement of system accessibility, there are distance-based, gravity-based, and utility-based models (Malekzadeh and Chung, 2020). The distance-based model is the simplest method in transit accessibility as it simply incorporates the distance from a given origin to different opportunities into the model. Some studies have proposed simple straight-line (Euclidean) distances, while others have proposed complicated impedance formulations for weighting the distance to opportunities (Geurs and van Wee, 2004) and (Makrí and Folkesson, 1999), as cited in (Malekzadeh and Chung, 2020). The gravity-based models propose a weight to opportunities representing their attraction and apply an impedance value (decay function) to reflect their distance from the origin (El-Geneidy and Levinson, 2006). The utility-based models are defined based on the "logsum" expression of a random utility model, in which the probability of an individual making a particular choice is related to the utility of all available choices (Ben-Akiva et al., 1985) as cited in (Malekzadeh and Chung, 2020). However, the model with distance-based measurement cannot capture the subjectivity in travel behavior. The gravity-based has some points of weakness that are similar to the distance-based. These models have difficulty calibrating their decay functions to capture traveler behavior for accessing transit services (Malekzadeh and Chung, 2020).

The utility-based is incorporated individual traveler preferences as part of the accessibility measure. This measure imitates human choice since the attractiveness of each destination is included. It is based on the economic benefits that people derive from accessing certain activities. This measure has several advantages, yet its complexity and data intensity are the main barriers to implementing it (El-Geneidy and Levinson, 2006). Therefore, applying utility models which consider all the benefits that travelers can gain from the choice of destination or land-use supply can provide a more accurate estimation of transit accessibility from the transit user's perspective (Malekzadeh and Chung, 2020). The BRT system in the study area is at an earlier stage and only has eight stop locations, we doubt the distance-based or gravity-based model is enough to simulate further development. Instead, we noticed the advantage of the utility-based model that can help explain the "subjective choice" of the users on their first transit system. It is supported by the fact that the previous public transportation angkot has been abandoned because conditions are uncomfortable and unattractive, although angkot has an advantage in terms of flexibility of stop locations.

Composite Accessibility Measure (Miller, 1999) as cited in (El-Geneidy and Levinson, 2006) is the combined distance-based and utility-based measures in one measure. However, this approach introduces a higher level of complexity where time constraints are superimposed and requires more data that utility-based and accordingly generalizing it for usage is not an easy task. To get the advantage both of an objective view of distance-based and a subjective view of utility-based measure, we realize the composite measurement is the most suitable in the study area. To help the complexity measurement of composite models, we found that GWR is suitable for dealing with the complex correlation of accessibility criteria on spatial-based data.

The shortcomings in measuring accessibility are indications of influential criteria that can cover all aspects of spatial to urban socio-economic, which require quite a lot of data and high computing in the modeling (Liu and Zhu, 2004). To overcome this combined data collection method is used. First, an on-board survey was conducted to get detailed field data. The survey begins with the surveyor boarding a BRT at the origin. While the BRT is traversing its route, the surveyor records the time of movement. The surveyor also records the number of passengers boarding or alighting the BRT at certain points along the route. Therefore, it would comprise the time the BRT moved or stopped and the number of passengers who boarded and alighted the vehicle at a point along the route. The survey terminates once the BRT reaches its end destination (Abad and Fillone, 2014).

Field data are verified and combined using crowdsourced data such as Openstreetmap (OSM). The use of crowdsourcing data in the field of transportation engineering could help with complex modeling that requires temporal and spatial data (Kumarage, 2018). Several studies have found that, compared to data from sources such as NMAs, OSM has attained a very high and mature level of completeness and spatial accuracy for various regions of the world (Dorn et al., 2015) as cited in (Foody et al., 2017).

Data collection results are managed in the form of the Road Network Dataset or Network Dataset. A network dataset is an abstract representation of the components and characteristics of transportation networks in the real world. One of the technological developments in modeling objects spatially is the GIS which has a spatial analysis approach to transportation networks called network analysis. In carrying out the network analysis, data in the form of an accurate road network dataset is needed (Sadeghi-Niaraki et al., 2011). ArcGIS is one of several software tools that can build, analyze and manage network datasets through network analysis tools. There are several preparing protocols to convert OSM data into ArcGIS Network Dataset. We cannot import OSM data directly into ArcMap or convert OSM format (.osm) to ESRI Shapefile (.shp). Importing OSM data directly into a network dataset without preparation can reduce the data quality. This conversion process results in data loss, which leads to an incorrect representation of road networks, particularly at intersections (Masoud and Idris, 2018).

Several previous studies attempted to construct a system accessibility model. (Malekzadeh and Chung, 2020) conducted a review of research on modeling the accessibility of modern public transportation, including BRT. Several models of accessibility of transit systems, such as Public Transport Accessibility Level (PTAL), Ideal Stop Accessibility Index (ISAI) and Actual Stop Accessibility Index (ASAI), Stop Coverage Ratio Index (SCRI) by (Foda and Osman, 2010, 2008) for example, has the same objective to capture system accessibility using a distance measurement. Another different approach in system accessibility modeling using utility-based measurement is the Environmental Transit Accessibility Index (ETAI) developed by (Rastogi and Krishna Rao, 2003) and (Rastogi and Rao, 2002), which is based on the subjective choice of stops by passengers. However, most previous studies in system accessibility modeling attempt to evaluate the existing system already developed in their study area. This study had a different purpose as the model was obtained for planning a new optimized system. Besides, GWR had an advantage in the enormous scope of criteria measurement in composite method, visual-spatial model output, and simulation, which is a relatively new approach.

Geographically Weighted regression (GWR) in transportation-related studies

GWR was the development of a regression model in which each parameter was calculated at each location point, so each geographic location point had a different regression parameter value. The GWR model was a development of the global regression model where the basic idea was taken from non-parametric regression (Mei et al., 2006). The GWR mathematical model can be seen in Equation (1).

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i)x_{ik} + \varepsilon_i \tag{1}$$

Where (u_i, v_i) are the coordinates of the i point and $\beta_k(u_i, v_i)$ is the result of the continuous function $\beta_k(u_i, v_i)x_{ik}$ at the point i, making a surface of the parameter estimates showing any spatial variability. GWR can perform using a fixed and adaptive kernel approach and bandwidth optimization using Cross-Validation (CV) and Akaike Information Criterion Corrected (AICc) methods. The output significance values can compare to finding optimum models (da Silva and Mendes, 2018).

Before performing the GWR regression analysis, a global regression model must be built first. According to ESRI (https://desktop.arcgis.com), a simple Ordinary Least Square (OLS) is recommended to be built first. Previous research using GWR (Zhou et al., 2019) performed OLS to remove any outliers and compared their significance. The significant model for OLS can be determined using several methods. One of them is using best subset regression by comparing adjusted R^2 and Cp-Mallows values. Mallows proposed the Cp-Mallows criterion in 1972, where Cp minimum statistics are considered the best model (Hocking and Leslie, 1967). Another reference is that the best model based on Cp was the model with the closest Cp value to the number of variables in the model (Hanum, 2011). The Cp-Mallows value was calculated by Equation (2).

$$Cp = \frac{RSS_p}{\hat{\alpha}^2} - (n - 2p) \tag{2}$$

Where p is the number of variables in the regression, RSS is the residual sum of squares for the particular p-variate regression being considered, and $\acute{\alpha}^2$ is an estimate of α^2, frequently the residual mean square from the complete regression. Moreover, the spatial autocorrelation (Global Moran's I) for each spatial criteria needs to check to see a spatial dependency using Equation (3).

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2} \tag{3}$$

Where z_i is the deviation of an attribute for feature i from its mean $(x_i - \bar{X})$, $w_{i,j}$ is the spatial weight between feature i and j, n is equal to the total number of features, and S_0 is the aggregate of all the spatial weights. Several previous studies applied GWR in transportation-related studies, specifically in the accessibility of the BRT-related system. For reference, (Yang et al., 2020) researched accessibility and proximity effects of the BRT corridor on housing prices in Xiamen Island, China, resulting in BRT accessibility premiums and proximity penalties simultaneously exist in the housing market, and the BRT effect on housing prices is spatially heterogeneous. Furthermore, the output of GWR has more significant results than global regression. A similar approach on hedonic price models (Zhang et al., 2020) investigated the connection between the accessibility of the open-system BRT network and property values in Brisbane, Australia. Using an improved model of GWR called the Geographically Weighted Generalized Linear model (GWGLM) that specifically justifies the calibration for individual variables. However, although using a similar method and objective, the purpose of their study is different as it finds the connectivity of BRT accessibility and land/property value or hedonic price models.

The accessibility criteria of BRT stop locations

The accessibility criteria of BRT stop locations or system accessibility can extend from the measurement method. In this study, the composite measurement method is used. Thus, the criteria with an objective view from distance-based measurement and a subjective view from utility-based measurement can be involved. In the distance-based system accessibility modeling, several factors influence the location of the bus stop, including the travel time by walking to the bus stop (Foda and Osman, 2010, 2008), waiting time at the bus stop, and population density around the bus (Zhao et al., 2003), (Polzin et al., 2002) as cited in (Malekzadeh and Chung, 2020). In the urban scale and using a GIS environment (Stewart, 2014) identify these factors of accessibility, such as travel time, reliability, availability of mode interconnection, and cost.

Accessibility of BRT is generally defined physically and can be measured globally as a person's travel time from origin to destination using the BRT system. Accessibility criteria themselves globally can include costs or fees, passenger comfort, security, convenience, etc. However, physical accessibility criteria are essential, although they do not describe globally. The criteria for physical accessibility are walking time, which is measured by calculating the walking speed assumption of 4.39 km/h (National Research Council (U.S.). Transportation Research Board, 2000) as cited in (Rodríguez and Targa, 2004).

Institute for Transportation and Development Policy (ITDP) published on The BRT Standard 2016 indicates the exact location of a station is highly site-specific. The goal is to make the station as easy to access as possible and close to nearby origins and destinations as possible (Wright and Hook, 2007). Another criteria for the stop is waiting time, which is influenced by the headway in the design of the BRT system. Waiting time is an important factor that determines the overall quality of BRT. In developed countries, the ideal waiting time for buses is 5–10 min, with a maximum tolerance in the range of 10–20 min (Meakin, 2004). In some literature regarding the evaluation of BRT shelter locations, land price or land value is one of the indicators. For example, Transmilenio Bogota, with a walking distance of > 5 min from the BRT stop, can reduce land values (Rodríguez and Targa, 2004).

Mix-used entropy index is a method that quantifies the land-use model, which is that the more mixed types of land-use in one area can improve active transport viability (Handy, 2005) as cited in (Gehrke and Clifton, 2019). Mix-used entropy has a close relationship with accessibility, which is an interaction that occurs between the components of land-use and transportation. An area where the mix-use entropy index is high logically will also have a high accessibility value. Mix-use entropy index calculated using Equation (4).

$$EI = \frac{-\sum_{k=0}^{n}(Aij\ InAij)}{In\ N} \tag{4}$$

Where *Ei* is the mix-used entropy index, *Aij* is a comparison between land-use area *i* and total land-use area (*j*). *N* is the number of types of land-use in *j*. Another reference for accessibility criteria that is quite detailed in setting the position of the stop is The BRT Standard issued by ITDP. The minimum location of the bus stop is 26 m and ideally 40 m from the intersection. The distance between stops is not too far between 300 m to 800 m, with the most optimal distance between stops being 450 m (ITDP, 2016). We try to incorporate these site-specific criteria from the BRT standard, as it distance-based measurement and has a development impact on planning the new location of BRT stops.

Some references in utility-based criteria (Hsiao et al., 1997) analyze transit pedestrian accessibility using GIS and highlight a strong relationship between transit service ridership and walking access to transit services. Another reference is (Gan et al., 2005) proposed a system accessibility model using the Florida Transit Geographic Information System (FTGIS). Accessibility in this model is defined by the number of people served in the transit catchment area, a three-quarter mile buffer zone around the transit stops. A composite measurement method of accessibility conducted by (Irmawandari and Handayeni, 2019) using a walk and ride accessibility index on a rail-based local train in Surabaya, Indonesia, resulted in a high positive correlation of 0.99 between the number of passengers and accessibility index. These previous studies concluded that the number of passengers in utility-based measurement is the closest indicator to capturing transit accessibility. Another reason is that the output of the regression model can easily understand if the number of passengers becomes the dependent variable. This study aims to plan a new transit system that we hope can maximize the users of the transit system.

Table 1
Synthesized Variables.

Literature	Variables	Measurement	Symbol
(Hsiao et al., 1997), (Gan et al., 2005), (Irmawandari and Handayeni, 2019)	Number of passenger (people)	Utility-based	Y
(Polzin et al., 2002), (Meakin, 2004), (Stewart, 2014)	Waiting time (minutes)	Utility-based	X_1
(ITDP, 2016)	Distance of stops to the road intersection (m)	Distance-based	X_2
(ITDP, 2016)	Distance between stops (m)	Distance-based	X_3
(Handy, 2005), (Gehrke and Clifton, 2019)	Mix-used entropy index (index)	Utility-based	X_4
(Rodríguez and Targa, 2004), (Stewart, 2014), (Foda and Osman, 2010, 2008), (Malekzadeh and Chung, 2020)	Travel time by walking to stops/first mile (minutes)	Distance-based	X_5
(Malekzadeh and Chung, 2020)	Total travel distance/origin to destination (km)	Distance-based	X_6
(Polzin et al., 2002), (Zhao et al., 2003), (Gan et al., 2005), (Malekzadeh and Chung, 2020)	Population density (people/km^2)	Utility-based	X_7
(Rodríguez and Targa, 2004), (Stewart, 2014), (Malekzadeh and Chung, 2020)	Travel cost (IDR)	Utility-based	X_8
(Wright and Hook, 2007), (ITDP, 2016)	Potential trip generation/ADT (vehicle/day)	Utility-based	X_9
(Rodríguez and Targa, 2004), (Yang et al., 2020), (Zhang et al., 2020)	Land value (IDR/m^2)	Distance-based	X_{10}

Based on the literature review and previous studies related to the accessibility criteria for the location of the BRT stop, several variables synthesized can be seen in Table 1.

Research methodology and data

On-board survey

The daily passenger data of BRT in the study area is not officially available. The BRT system is at an early stage and still uses manual ticketing as this research was conducted. The on-board survey was performed to calculate the number of daily passengers at each BRT stop, as the data are needed for dependent variables in this study. The survey took the bus from the initial stop to the last stop in the study area and recorded the number of passengers on the bus, descending passengers, and boarding passengers.

There are two round-trip BRT routes in the study area, with each stop having four arrivals scheduled daily. The number of passengers used for analysis is the total of boarding and alighting passengers at each stop. The survey begins within the first schedule at the initial Nol-kilometer BRT stop. As scheduled, the bus will arrive at 7:30 a.m. After passing within four bus stops, the first route ends at Km.6 bus stop. In the last stops of the first route, the surveyor transit to go back to Nol-kilometer and wait until the first bus arrived at the second route. After passing six bus stops, the second route ends at the Nol-kilometer stop. The survey continued on the following bus schedule until the last schedule, estimated at 4:00 p.m. However, there is no reliable bus schedule at each stop. The officially published schedule is just the first and last departing time at the initial bus stop. The on-board survey is the initial data collection used to find the number of passengers variables. The route of the on-board survey can be seen in Fig. 2.

Questionnaire

Questionnaires were distributed to passengers during the on-board survey on the bus. However, it is quite difficult for passengers to fill out questionnaire forms during the trip, especially for passengers with short distances. So we do more direct interviews and help fill out the questionnaire form. We ensure the bus passengers get the questionnaires before descending and after boarding. Thus, the number of passengers within the on-board survey is the same as the number of respondents. This method is possible because the number of passengers is relatively small and the headway of the bus is very long (>2 h) so that when the bus arrives, all the passengers at the stop will get on the bus (the stop has become empty). Data from the questionnaire included passenger gender, job, age range, and travel purpose with anonymous identity for an overview. However, the essence of the questionnaire question is to answer the variable conditions.

The questionnaire is used to find the waiting time (X_1), the passenger's origin point before boarding to BRT stop, and the destination (O-D). Another question is the mode that passengers used to BRT stop (first-mile) and leaving BRT stop (last-mile) and their travel cost (X_8). However, because the BRT cost is flat, we notice the key difference in cost is at their first-mile and last-mile. The origin and destination (O-D) point of passengers can be converted into a spatial database that is used to draw other variables like travel time (X_5) and travel distance (X_6) using a network dataset. Other variables such as the Mix-used entropy index (X_4), Population density (X_7), Land value (X_{10}), and Potential trip generation (X_9) are compiled using combined O-D and secondary data.

Secondary and crowdsourced data

Secondary data were previously available data collected from indirect sources. Several secondary data were obtained in this study, including from government agencies such as land-use data, road classes, and related regulations. In addition to compiling road network datasets and verifying variables such as travel time, data sourced from passive crowdsourcing was also used in this study, including OpenStreetMap (OSM). ArcGIS Editor for OpenStreetMap is an ArcMap tool that supports using OpenStreetMap data inside ArcGIS. The tools can load.osm files, apply symbology, contribute data back to OSM, and create a network dataset from OSM data.

From a network dataset, variables such as distance of stops to the road intersection (X_2) and distance between stops (X_3) can be drawn. The O-D data of passengers can be converted into a point using geolocation services such as Google Maps API and validated data variables from questionnaires such as travel time (X_5) and travel distance (X_6). Another variable validated from a network dataset is travel cost (X_8) by assumed distance and mode used. An overlay of a network dataset with land-use characteristics such as land value, potential trip generation, and the mix-used entropy index can give robust data.

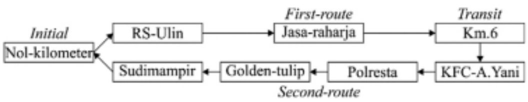

Fig. 2. On-board survey route.

Data preparation

This paper uses OLS to get significance criteria and perform the classical assumption test to obtain a significant mathematical model. The significant model for OLS is determined using best subset regression by comparing adjusted R^2 and Cp-Mallows values.

Classical assumption tests were conducted on the model, such as the heteroscedasticity test, autocorrelation test, multicollinearity test, and the normal distributed test for residuals. The global model result possibly contains non-spatial variables. The non-spatial variables were variables that do not have geolocation information in their data and cannot include in spatial analysis, such as GWR. As for getting the spatial analysis unit, the study area within the administrative boundaries was divided into a grid of 100 m × 100 m. The grid division resulted in 10,246 units with a total area of 10246 × (100 m × 100 m) = 102.46 km^2. The OLS performed again on spatial variables and the classical assumption test to get a global regression model.

The simulation of the GWR model in the study area was performed by considering the parameters in the GWR output, such as the condition value, standard error, local R^2, and the resulting predicted Y value. Furthermore, the sensitivity test was conducted by configuring variables spatially to see changes in the model, especially variables directly related to the operation of the BRT. The flowchart of this research methodology can be seen in Fig. 3.

Results and discussion

The global regression model

The on-board survey counted boarding and alighting passengers from eight BRT stops, resulting in total 137 passengers using BRT in a day within the study area. Nol-kilometer stop as the initial stop located downtown and surrounded by the commercial, office complex, and recreation land-use has the highest number of passengers. However, the lowest usage is at Sudimampir stops, although it is located in downtown and commercial area. This phenomenon slightly shows the influence of criteria that are quite broad and interesting to be analyzed further. The number of passengers at each stop can be seen in Fig. 4.

Using ArcGIS, a network dataset is built based on downloaded OSM data. As we compared the OSM, local government road data, and satellite imagery, OSM has more detail and reached 1091.86 km total road length compared to 790.13 km of local government data. We check the validity of network attributes such as one-way protocols, speed limit, intersection signal, U-turn restriction, etc. It will impact the calculation of travel distance and time. The O-D data of passengers from the questionnaire were converted into geolocation and plotted into a network dataset. We can see the distribution of passengers for each bus stop and plot the possible route passengers take to go to BRT stops using the combined fastest and shortest route method.

From the geolocation O-D, we can see that the distribution of passengers in the study area can reach far, with the farthest distance being 6 km. However, there is diversity in the mode passengers use to reach or leave BRT stops, as the farthest passengers use a car and motorcycle, and the shortest distance is just by walking. To equalize this, we convert the distance to walking time using a 4.39 km/h standardized walking speed (National Research Council (U.S.). Transportation Research Board, 2000). The plotted O-D data can be seen in Fig. 5.

The distance-based variables such as distance of stops to the road intersection (X_2) and distance between stops (X_3), and land-use characteristic variables such as Mix-used entropy index (X_4), Population density (X_7), Potential trip generation (X_9), and Land value (X_{10}) can be calculated based on grid unit. Then variables condition at each bus stop and passenger's O-D point can be extracted for OLS analysis. Spatial variables can be calculated based on grid units, as shown in Fig. 6.

The results of OLS regression simultaneously on all variables showed that only three variables rejected the null hypothesis with a p-value > alpha 0.05 out of a total of 10 predictive variables. In addition, several variables with high Pearson correlation values (>0.5) also failed to reject the null hypothesis. Thus, optimizing the model using the best subset regression by comparing the adjusted R^2 and Cp-Mallows values on all possible paired variables was necessary. The model selection results with the best subset regression can be seen in Table 2 (selected models in bold and italic).

As the rule of best subset, the maximum adjusted R^2 and the minimum Cp-Mallows value were selected as the best model. Three variables were eliminated in the selected model as it failed to reject the null hypothesis (p-value < alpha 0.05). However, the selected variables in the best subset need to be statistically validated using the classical assumption test. The results of the assumption test can be seen in Table 3.

Based on the OLS and classical assumption test results, the criteria for the accessibility model of BRT stop locations in the study area include waiting time (X_1), the distance of stops to the road intersection (X_2), the distance between stops (X_3), mix-use entropy index (X_4), travel time by walking to stops/first mile (X_6), population density (X_7) and land value (X_{10}). The global regression model can be seen in Equation (5).

$$Y = -20.198 + 0.229X_1 - 0.040X_2 + 0.005X_3 + 5.292X_4 - 0.159X_6 + 0.00045187X_7 + 0.00000893X_{10} \quad (5)$$

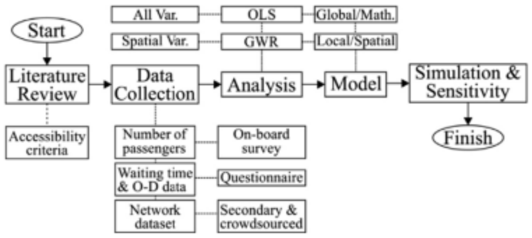

Fig. 3. Research flowchart.

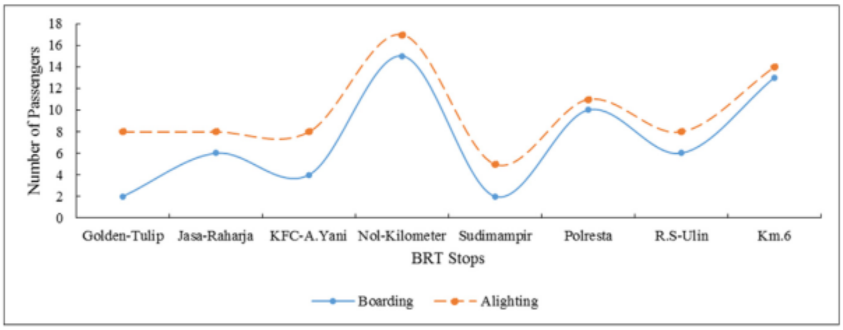

Fig. 4. The number of passengers (On-board survey on February 27, 2021).

As we can see from the mathematical model, the mix-used entropy index (X_4) has the highest coefficient with a positive sign. It can be interpreted that the mix-used entropy index has the most significant influence in describing the number of passengers as it means the BRT stop locations accessibility. The positive sign described its influence direction as linear; if we increased the X_4 value, it would increase accessibility. We can look back to the data, as the location of the Nol-kilometer stop is surrounded by multiple land-use at downtown, with the highest number of passengers. The lowest coefficient is the land value (X_{10}). Although it has a positive sign, we can assume that as the BRT development in the study area is at an earlier stage, it has not yet had a strong impact on land values.

The variable with a negative coefficient is the distance of stops to the road intersection (X_2). As we do not expect it, this phenomenon can explain the nature of the utility-based variable. The passengers are more prefer the stop location near the road intersection. Theoretically, the intersection is the nodes of the road network that have more accessibility, although it had a negative impact on BRT's operations. The negative sign for total travel distance/origin to destination (X_6) is reasonable. As far as the travel distance, the accessibility decreased. This result explains that the passenger prefers short-distance travel using BRT.

The potential trip generation (X_9) is failed to reject the null hypothesis and not included in the model. As the data are based on the assumption of average daily traffic of land-use characteristics, we do not expect it to be rejected. However, we assumed that the land-use characteristic in the study area has a weak relationship with the traffic generation assumption.

The GWR model

The spatial model of BRT stop locations was built using GWR. However, the global model's OLS result includes non-spatial variables that could not be arranged into grid cells, such as the waiting time (X_1) and the distance between stops (X_3). The GWR model was built based on spatial variables, including the number of passengers (Y), the distance of stops to the road intersection (X_2), mix-use entropy index (X_4), population density (X_7), potential trip generation (X_9) and land value (X_{10}). The OLS was performed on the spatial variables to get the global model. The output was relatively similar to non-spatial included OLS, where the X_9 variable failed to reject the null hypothesis. However, the global model significance or adjusted R^2 decreased to 0.861 from 0.964 because of the missing non-spatial explanatory variables. The global model of spatial variables can be seen in Equation (6).

$$Y = -9.688 - 0.016X_2 + 27.088X_4 + 0.00028X_7 + 0.0000048X_{10} \quad (6)$$

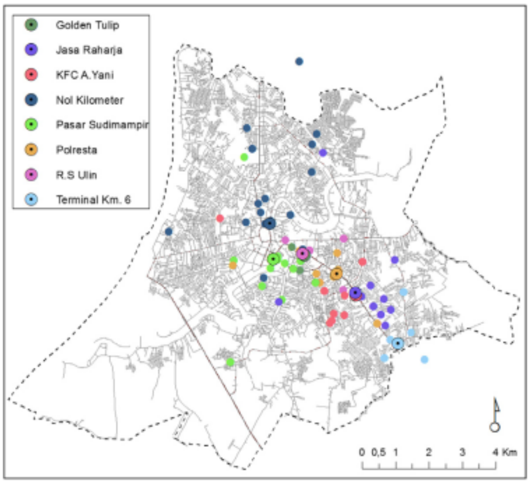

Fig. 5. The passenger's O-D and BRT stop locations.

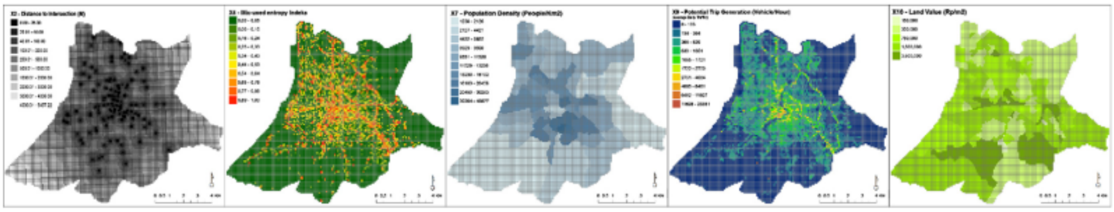

Fig. 6. Spatial Variables (From left to right: X_2, X_4, X_7, X_9, X_{10}).

Before GWR was performed, the spatial autocorrelation (Global Moran's I) was conducted to see each variable's spatial dependency. Using ArcGIS, the test results showed the index value of each of these variables > 0.05, p-value < 0.01. The critical value (z-score) of each variable was greater than 2.58. There is less than a one percent likelihood that the clustered pattern results from random chance, which indicates a spatial dependency for all variables. Tobler's first law of geography can interpret these results, "Everything is related to everything else, but near things are more related than distant things."

GWR analysis was performed using ArcGIS and considering the parameters in the GWR output, such as the condition value, standard error, local R^2, and the resulting predicted Y value. There are several kernel approaches and bandwidth optimization in GWR, as we compare fixed and adaptive kernel and bandwidth optimization with AICc and CV. Based on the global model, we assumed the adaptive kernel has more advantage in maximizing their model significance by looking at high variance in data variable and distance location of each BRT stop. However, comparing the parameter's output is the best approach to selecting the model. The parameters output of GWR can be seen in Table 4.

The bandwidth used in Fixed AICc is 2711.97 m and based on the distance of each BRT stop location, it can reach the location of the neighboring BRT stop. However, in Fixed CV the bandwidth distance is relatively small at 52.94 m, and it could not reach the neighboring location. The adaptive AICc has no bandwidth output information as the bandwidth value is adjusted in every stop location until it reaches its neighbor. Based on the adjusted R^2 value, the AICc bandwidth optimization has better significance, and as the AICc finds the optimum AIC value, it has the smallest AICc output over CV. The adaptive kernel resulted in the highest adjusted R^2, although Fixed AICc has the smallest AICc output. The chosen model is the adaptive AICc as it has more advantages of simulation in the study area with an adjusted bandwidth value. The chosen GWR model can be compared with a global model of the spatial variable before, resulting in GWR having a significant value that can be seen in Table 5.

Based on key output parameters, the GWR has a higher adjusted R^2 and smallest AIC. This result explains that the accessibility model of BRT stop locations has spatial influence that can be better explained in GWR than in the global model. Furthermore, GWR produced a local regression model at each BRT stop location with different values that consider each location's variable conditions, as seen in Table 6.

Table 2
Best Subset Regression Results.

Variables	Adjusted R^2	Cp-Mallows
X_9	0.383	167.363
X_9 / X_{10}	0.632	89.252
X_6 / X_9 / X_{10}	0.848	29.821
X_1 / X_6 / X_9 / X_{10}	0.869	23.853
X_2 / X_3 / X_7 / X_8 / X_{10}	0.919	12.764
X_1 / X_2 / X_3 / X_6 / X_7 / X_{10}	0.942	8.907
X_1 / X_2 / X_3 / X_4 / X_6 / X_7 / X_{10}	***0.964***	***6.018***
X_1 / X_2 / X_3 / X_4 / X_5 / X_6 / X_7 / X_{10}	0.963	7.449
X_1 / X_2 / X_3 / X_4 / X_5 / X_6 / X_7 / X_9 / X_{10}	0.959	9.150
X_1 / X_2 / X_3 / X_4 / X_5 / X_6 / X_7 / X_8 / X_9 / X_{10}	0.952	11.000

Table 3
Classical Assumption Test Result.

Test	Output	Interpretation
Heteroscedasticity	p-value = 0.231 or > 0.05	Residuals were homoscedastic
Autocorrelation	p-value = 0.523 or > 0.05	No autocorrelation in the residual
Multicollinearity	VIF value < 10	No multicollinearity between independent variables
Normality	p-value = 0.623 or > 0.05	Residuals were normally distributed

Table 4
Parameter of Output GWR.

Parameter	*Fixed AICc*	*Fixed CV*	*Adaptive AICc*
Bandwidth	2711.97	52,94	-
Residual Squares	11.683	32.56	6.432
Effective Number	6.504	5.005	7.107
Sigma	2.795	3.297	2.684
AICc	−7,631,30	130.2	−133.70
R^2	0.978	0.939	0.988
R^2 Adjusted	0.897	0.857	0.905

Table 5
Significance of global model and GWR model.

Parameter	OLS Regression (Best subset)	GWR (Adaptive AICc)
R^2	0.940	0.988
Adjusted R^2	0.861	0.905
AIC	21.017	−133.700

Table 6
A local model of GWR.

BRT Stop Locations	Local Model of GWR
Nol-Kilometer	$Y = -10.189 - 0.024\ X_2 + 19.531\ X_4 + 0.0007\ X_7 + 0.000002\ X_{10}$
RS-Ulin	$Y = -9.607 - 0.024\ X_2 + 18.533\ X_4 + 0.0007\ X_7 + 0.000002\ X_{10}$
Golden-Tulip	$Y = -9.487 - 0.024\ X_2 + 18.344\ X_4 + 0.0007\ X_7 + 0.000002\ X_{10}$
Sudimampir	$Y = -9.947 - 0.024\ X_2 + 19.038\ X_4 + 0.0007\ X_7 + 0.000002\ X_{10}$
Polresta	$Y = -5.94 - 0.021\ X_2 + 14.882\ X_4 + 0.0007\ X_7 + 0.000001\ X_{10}$
Jasa-Raharja	$Y = -4.346 - 0.02\ X_2 + 16.039\ X_4 + 0.0003\ X_7 + 0.000005\ X_{10}$
KFC-A.Yani	$Y = -4.458 - 0.02\ X_2 + 16.129\ X_4 + 0.0003\ X_7 + 0.000005\ X_{10}$
Km.6	$Y = -3.676 - 0.021\ X_2 + 13.636\ X_4 + 0.0003\ X_7 + 0.000006\ X_{10}$

Model simulation and sensitivity

The advantage of the GWR model is that it can be simulated through the study area and results in a visual-spatial model rather than only a mathematical model. The visual-spatial model can be better understood, and the location information is helpful in decision making, planning, and development of the new BRT corridor. Simulation performed using ArcGIS and chosen GWR model with adaptive kernel and AICc Bandwidth optimization.

The simulation output has a parameter to consider. The output has 66 grid cells with condition values > 30. As a rule of thumb of GWR simulation, do not trust results for features with a condition number larger than 30, equal to Null or for shapefiles, equal to −1.7976931348623158e + 308 (https://desktop.arcgis.com). We eliminate that 66 grid cells from the output simulation. The standard error value tended to be greater in urban-periphery areas, as the location of BRT stops only in the downtown area. The model has low adaptation to variable conditions in urban-periphery areas. The local R^2 value was in the range 0.84 – 0.99, where this value was above the average and significant (>0.5). There was a predicted value in the negative range (-), so adjustments were made by eliminating the cells as the negative predicted value mean predicted number of passengers (Y). We considered that area had no accessibility value for BRT stop locations. The GWR simulation parameter output can be seen in Fig. 7.

For more informative results, the level of accessibility measured by the number of passengers or predicted Y could be classified into five classes: very low, low, moderate, high, and very high. The classification was calculated using a natural breaks (Jenks) approach, as shown in Fig. 8.

From the model, we can see the BRT stop location with very high accessibility widespread on the arterial road of the study area. We can divide an area with very high accessibility into two clusters for corridor development. First is an area with a high potential for corridor development but lacks the main infrastructure such as pedestrian connectivity. The eastern part Sungai-Lulut is a suburban area growing rapidly due to low-priced housing development. On the main road corridor, there is also a supporting commercial area. However, as land-use grows rapidly, the development of transportation is inadequate. Where almost every peak hour, there is congestion due to private vehicles. The western part has potential through the HKSN road corridor. An alternate is through the Teluk-Dalam road corridor as it is connected with the port of Trisakti. However, the western corridor had a natural barrier development of the Barito River. The southern part has potential through a new ring road corridor, Basirih, and connected to Gubernur Soebardjo Ring-road. However, the ring road connection is still developing and has limited service.

The second cluster is an area with a high potential for corridor development and has the main infrastructure such as pedestrian connectivity. The area in this cluster is the northern part through the Kayu-Tangi road corridor or Brigjen H.Basri road and the central area through the Gatot-Subroto road corridor. The northern area had high potential passengers from schools, universities, and office-complex and the Gatot-Subroto road corridor is a high-density commercial corridor.

The sensitivity test of the model was performed by gradually intervening on variables. In this case, the distance of stops to the road intersection (X_2) was chosen as it is directly related to BRT operations and is most realistic for spatial intervention. The simulation is performed by gradually increasing the distance of the BRT stop location from the road intersection. Based on the BRT standard, the minimum distance was 26 m, and the ideal was 40 m from the intersection. We choose three BRT stops: Golden-tulip, Sudimampir, and Polresta, as their existing location is below 26 m from the intersection. The sensitivity test parameters are in Table 7.

The output of this sensitivity test can be broadly seen in the predicted Y value. There has not been a significant change in the first and second parameters as the new location is still in the same grid cells and only the value of X_2 changes. However, in the third parameter, there is an increase in accessibility at the three stops, but in the fourth parameter, there was a decrease in value at two BRT stops. The comparison of values at each bus stop can be seen in Fig. 9.

In the model before, the X_2 variable has a negative coefficient value which means it has the opposite value to accessibility. However, in this sensitivity test, increasing the distance of the BRT stop with the intersection at specific parameters (50–100 m) could increase the value of its accessibility. Although, the predicted Y value dropped at the last parameter above 100 m. Besides the changes in mathematical value, we can see the changes in the spatial pattern of each parameter in Fig. 10.

As discussed in the mathematical model before, there was no significant change in the first and second parameters. However, in the GWR spatial pattern, we can see changes in the southern area, specifically in the intersections of the south ring road, one of which was caused by the increasing value of the criteria range for the X_2 variable. It can be concluded that the areas with the main intersection are become overestimated in the model.

In the third parameter model of the sensitivity test, there was a widespread area in the intersection node of the main roads even though the value was in relatively low classes. However, the periphery of the southern area was drastically becoming an area with vast potential for BRT accessibility. This phenomenon can explain the urban growth of the study area

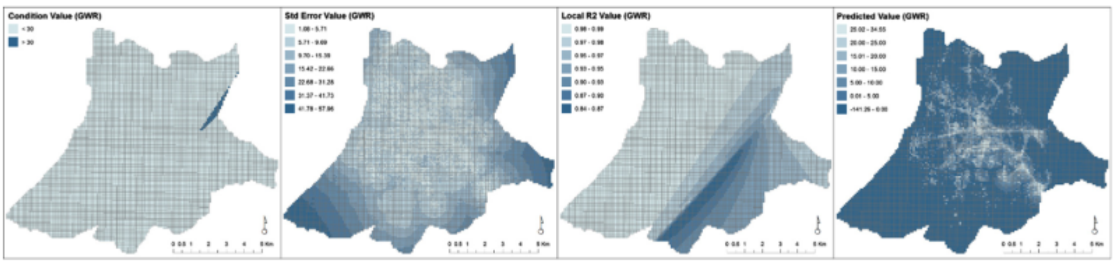

Fig. 7. Simulation Output (from left to right: condition, std. Error, Local R^2, and pred. value).

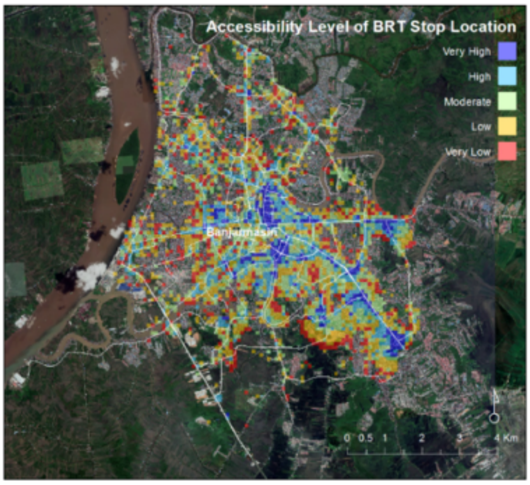

Fig. 8. Accessibility Level of BRT Stop Locations.

Table 7
Sensitivity Test Parameters.

Parameter test	Distance of X_2 (m)	Grid Cell
1st parameter	0–25 m	No shift
2nd parameter	25–50 m	No shift
3rd parameter	50–100 m	Shift by 1 cell
4th parameter	100–150 m	Shift by 2 cells
n^{th} parameter	+50 m	Shift by n – 2 cells

represented by the variable of this research has a potential development direction to the southern area. The southern area had fewer natural barriers, such as large rivers like the Alalak River in the north, the Martapura River in the east, and the Barito River in the west. The existence of a ring road (Gubernur Soebardjo road) and the railroad development plan in the southern area are other supporting facts that the southern area had the highest potential.

Furthermore, this result can be a consideration for developing the city and its transit system in the study area. Meanwhile, in the fourth parameter, the widespread area becomes unnatural, as the accessibility is only based on the distance radius of the road intersection. The high range of X_2 variables leads to underestimating other variables in the model.

Conclusions

From the results, it can be concluded the spatial criteria which affected the accessibility of BRT stop locations in the study area were the distance of stops to the road intersection (X_2), mix-used entropy index (X_4), population density (X_7), and land value (X_{10}). The global regression model using OLS resulted in 0.861 of R^2. The spatial autocorrelation (Global Moran's I) test reports spatial dependency on all spatial variables. Using the adaptive kernel and AICc bandwidth optimization, the GWR model resulted in a higher significance R^2 value of 0.905. Furthermore, the AIC of GWR has a smaller value of −133.700 than 21.017 in the OLS model. The results can be evidence of strong consideration that the GWR is better in modeling accessibility of BRT stop location in the study area with spatial dependency in its criteria. We found that the most influential criteria from the model are the mix-used entropy index (X_4). GWR simulation produces a visual-spatial model and shows that the new BRT corridor development in the study area can be divided into two clusters.

The concept of accessibility itself continues to evolve and produce new measurement and modeling methods. In this paper, we found that the complexity in composite accessibility measurement can be solved by the regression equation of GWR with easy-to-understand output. The model can incorporate both the objective view of urban variables and the subjective view of passengers. Furthermore, instead of just measuring and modeling the existing accessibility of transit systems, GWR had an advantage in simulation to forecast optimized future transit systems.

The method and output in this paper can help the early-stage development of transit systems, specifically the BRT system. Although the BRT system is the easiest to implement, it also has many failure factors that make it abandoned by passengers. BRT's nature that uses existing infrastructure requires a solid study of accessibility in determining new corridors. The

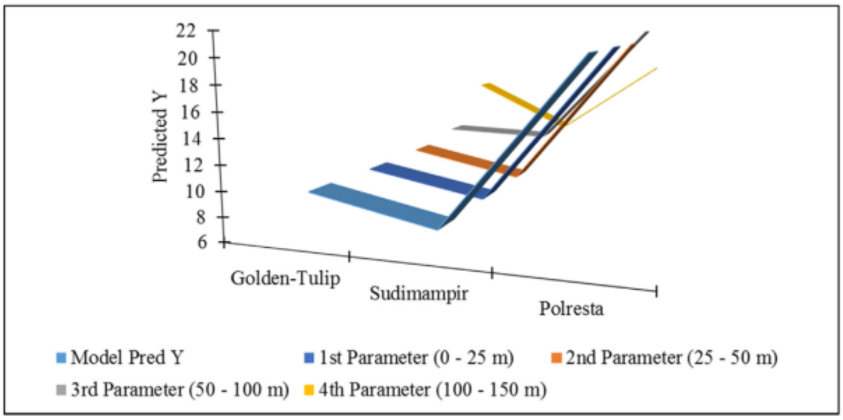

Fig. 9. Sensitivity test.

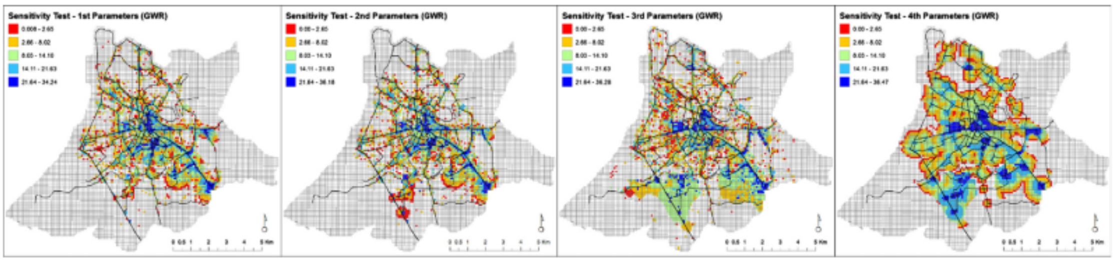

Fig. 10. Sensitivity Test Spatial Pattern (from left to right: Parameters 1, 2, 3, and 4).

accessible and effective transit corridor will reduce the usage of private transportation. Hence, this study can become an alternative reference to help policymakers plan sustainable transportation.

However, this paper still needs a lot of improvement. The independent variables crucial to the results can be improved using time-series data, especially if the BRT ticketing has used an electronic system to automatically count the number of passengers at each stop. Furthermore, the non-spatial variable can transform into the spatial variable if sufficient geolocation data are included in the GWR model.

Conflict of Interest

All the authors have no conflict of interest with the funding entity and any organization mentioned in this article in the past three years that may have influenced the conduct of this research and the findings.

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