THE SPATIAL AND SOCIAL PATTERNING OF HEALTH CARE FACILITIES IN GREATER JAKARTA, INDONESIA

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ABSTRACT: The distribution of health facility location has a direct impact on the community; inaccessible health care facility is more likely to increase the risk of morbidity and mortality for some cases, while also provoking public discontent. The local governments and health facility providers need to understand the spatial characteristics of the distribution of health facilities related to the social and demographic conditions of the community. This study aims to explore information about the spatial and social patterning of the health care facility located in Greater Jakarta, Indonesia. Spatial analysis using the Geographically Weighted Regression (GWR) method was conducted to detect the relationship between the distribution of health facility locations and the social and demographic characteristics of the community. Geographical Information System is used as the main approach to compile, edit, visualize, and process spatial and attribute data. Geographically Weighted Regression proved that the current distribution of health facility locations has a significant relationship with the population. Furthermore, the population data is generated into spatial weights for the spatial autocorrelation analysis, using the local indicator of spatial association (LISA) to identify the spatial clustering of healthcare facility locations. Spatial autocorrelation analysis calculates the Moran's I index which identifies areas that are significantly clustered or outliers. The outliers within the studied area show a high number of the population with a low number of health care facilities, or some areas with a relatively high number of health care facilities with a low population. This finding identified improvement needed to gain the equal distribution of health care facilities based on the population distribution to increase public access to health care and reduce inequities. This knowledge is important to develop effective location-based strategies to determine the health facility location, to improve the overall health care system, which will directly improve public health.

1. INTRODUCTION

Health is considered to be a fundamental human right and a major area of global social and political concern (WHO, 2017). Human health can affect many aspects of human life, studies also suggest that poor health and poverty are mutually dependent (Peters et al., 2008). The proximity of the location between the community's residence and the location of the health facility provides convenience for the community to obtain health services. Access to health care is vital and is considered a precondition for the overall success of the health system of a country (Black et al., 2004). The health care facility is one of the public facilities whose development focus is to increase public access to health care and reduce inequities. The distribution of health facility location has a direct impact on the community; an inaccessible health care facility is more likely to increase the risk of morbidity and mortality for some cases, while also provoking public discontent. Determining the location of health facilities that follows the needs of the community and contains many advantages and ease of access is very important. In addition to designing the system, layout, and services provided, another important thing in the planning process of a health care facility is determining the location of the facility.

Health care accessibility is a multidimensional concept that is defined as a population's ability to obtain health care services (R. M. Andersen, 1995; Wang & Luo, 2005). The concept of accessibility does not limit itself to distance measures, but also subjective measures (Comber et al., 2011). Health care accessibility generally talks about four dimensions of access: availability, geographical dimension (physical location), affordability, and acceptability (O'Donnell, 2007; Peters et al., 2008). Another disaggregation of the dimensionality of health care accessibility includes geographical (which relates to time and distance between service providers and the consumers) and aspatial (which relates to elements such as class, age, sex, health-seeking behavior, cultural traits, the knowledge of health and health care which may act as a determinant of health care access) (Edusei & Amoah, 2014; Levesque et al., 2013; Wang & Luo, 2005). The geographical dimension itself can also be understood using multiple contexts, namely the relationship between the spatial separation of the population and the supply of health care facilities (Ursulica, 2016), a measure of the distance and its restrictions (such as travel time, distance to facilities, and the quality of roads) (Delamater et al., 2012; Edusei & Amoah, 2014), and the representation of the capacity of health facilities relative to the size of the target population and how physically accessible the facilities are to the population (service accessibility) (Munoz & Källestål, 2012). This paper discusses accessibility in terms of the distribution of health care facilities within a certain region (which relates to their availability and is interpreted by location data) and their relationship with several demographical characteristics within the area.

Accessibility to health care is influenced by classified levels of care and spatial characteristics of the population and health care facilities. The location of health care services is significant in assessing the unmet medical needs of a population (Zhang et al., 2019). An illogical health care location decision that leads to an inaccessible health care facility can have multiple negative effects on society that don’t just concern the simple cost and service metrics — it is also associated to increase the risk of morbidity and mortality, while also provoking public discontent (Ahmadi-Javid et al., 2017). Moreover, when health care services are needed but are delayed or not obtained, people’s health worsens, which in turn leads to lost income and higher health care costs, both of which contribute to poverty (Narayan et al., 2000; Smith, 1999).

Many communities in developing countries tend to have less access to health services despite the frantic efforts by governments and tremendous policy aids from the international community to improve health conditions (Atuoye et al., 2015; O’Donnell, 2007; Peters et al., 2008). The problem of accessibility to health care in developing countries manifests in two folds. The supply side faces a challenge in the provision of health care facilities and the inadequacy of resources that leads to missing quality and effective services from the available facilities. The demand side faces a challenge in the form of how the people may not get access to health services from which they could benefit (Mooney, 1983). Hence, there is a need for health care policymakers to be sensitive to the location of health care services and the distribution of health care types, since usually health care facilities are concentrated in urban areas which shows a significant relationship between population and health care distribution (Babatimehin et al., 2014; Mustapha, 2017). The findings of this study can be used to better understand the current spatial characteristics of health care facilities as input to further improve the overall health care system.

The objectives of this study are to detect the relationship between the distribution of health facility locations and the social and demographic characteristics of the community using the Geographically Weighted Regression (GWR) method and to identify the spatial clustering of healthcare facility locations by calculating the Moran’s I index and generating the cluster map. This article discusses the study by organizing content as follows. The introduction section explains the urgency to develop health care facilities in the context of location proximity to the presence of the community. The next section describes the data used and the methods that will be used to achieve the research objectives. Section 3 discusses the study results. The last section concludes the findings and identifies the possibility of future research.

2. METHOD

The object of this study is health care facilities which include Public Health Centres (PHC) and accredited hospitals within the greater area of Jakarta. Figure 1 shows the stages of research conducted in this study. Spatial data used in the study was obtained from various sources. The main data collected is health care location data. The data was obtained from the official website of the Indonesian Ministry of Health, Central Bureau of Statistics, and the data portal "Open Data Jakarta", including information on names, categories, and addresses of health care facilities. Google Maps API was used in the geocoding process from the address data, as well as resolved and validated incomplete data from health care facilities obtained data.

The socio-demographic data collected were from the year 2017-2018. The data collected includes population, gender ratio, percentage of employment, and percentage of population education. These variables relate to the aspatial elements that also determine access to health care, this is especially important because apart from the geographical/spatial factors, aspatial factors are deemed equally important (Wang & Luo, 2005). The male/female gender ratio is identified as one of the observed variables to examine the existence of gender gaps related to health care accessibility within the studied area. Previous research showed that the gender gap mainly affects females when the health care cost is relatively high and is associated with a poor socioeconomic situation (Portela & Campos Fernandes, 2014). Other biological or environmental differences among population groups also affect the ease of access to health care services. Education and age groups are also associated with the use of healthcare (*Health-Care Utilization as a Proxy in Disability Determination*, 2018). Differences in knowledge or education levels are reflected in disparities in health care utilization (O’Donnell, 2007). The number of population also identified as the observed variable to examine the relationship between the health care and the population distribution because both health care professionals and the population are not uniformly distributed and hence health care accessibility would vary across space (Ursulica, 2016; Wang & Luo, 2005).

The scope of the research area is the Greater Jakarta Area, which covers 10 regions: Central Jakarta, East Jakarta, North Jakarta, West Jakarta, South Jakarta, Kepulauan Seribu, Bogor, Bekasi, Depok, and Tangerang. This study aims to evaluate the spatial equity of the health care facilities available in the Greater Jakarta Area. The data that has been collected, including area boundaries, health care facilities location, and socio-demographic data, is managed using a Geographic Information System approach. Pre-processing data consist of setting the projection system as well as completing attribute data collected from various sources. To support the spatial data processing that will be applied, the coordinate system is transformed from WGS84 (EPSG:4326) to WGS 84/UTM zone 48S (EPSG:32748).

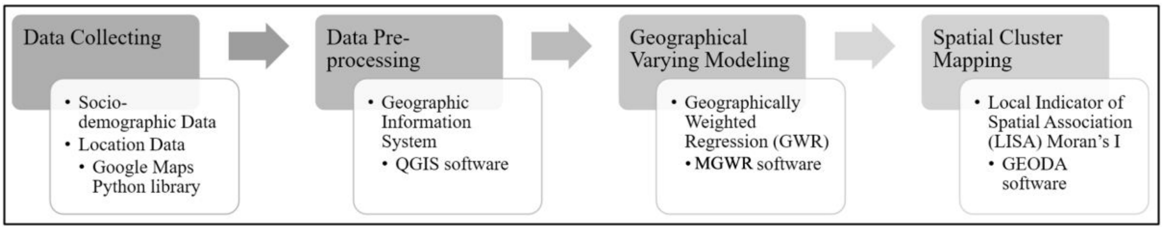

Figure 1. Research stage flowchart

Figure 2 shows the initial visualization of the population distribution of each district. The visualization shows how the population is distributed across the study area, represented by the red-green spectrum, in which areas with denser populations are represented by the color red and areas with more diffused populations are represented by the color green. The distribution map of all health care facilities, hospitals, and public health centers throughout the studied area can be seen in Figure 3.

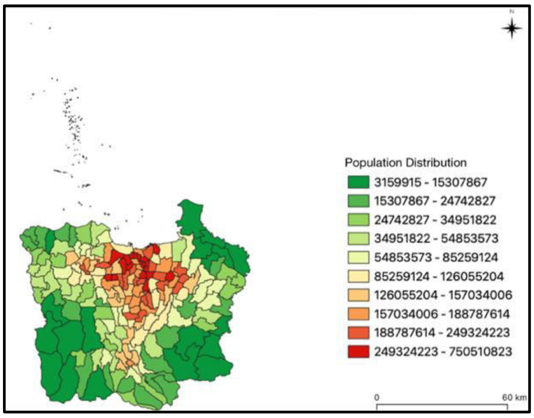

Figure 2. Population density mapping within Greater Jakarta Area

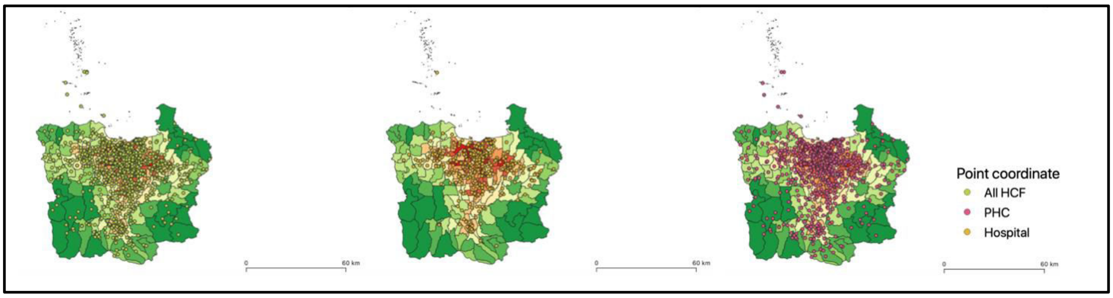

Figure 3. Population density mapping within Greater Jakarta Area with a distribution of all health care facilities, public health centers, and hospitals.

The next stage of the research is geographical varying modeling. The Geographically Weighted Regression (GWR) is a regression model which accounts for how dependent variables are influenced by location. It is an important local tool to explore spatial heterogeneity in data relationships (Lu et al., 2014). GWR presents an exploratory platform to reveal the existence of relationships between variables and the criterion variables across space within a single framework (Nkeki & Osirike, 2013). The process used MGWR 2.2 which was developed by Spatial Analysis Research Center (SPARC) of Arizona State University.

The model to be used in the analysis is the Gaussian Model, which is the conventional GWR model, as shown in equation (1).

$$y_i = \beta_0(u_i, v_i) + \sum_j \beta_j (u_i, v_i) x_{ij} + \varepsilon_i \quad (1)$$

It is defined that $\beta_0(u_i, v_i)$ is the intercept, x_{ij} is the jth predictor variable, $\beta_j(u_i, v_i)$ is the jth coefficient, ε_i is the error term, and y_i is the response variable. This model is based on the assumption that there are n observations, for observation $i \in \{1,2,...,n\}$ at location (u_i, v_i) (Oshan, T. M. et al., 2019),
The model will use Fixed Gaussian Kernel which is one of the classic options of geographical kernel type for GWR models. The Gaussian kernel is suitable for fixed kernels because it can avert the risk of the existence of data with no kernel since it weights continuously and gradually decreases from the center of the kernel but the value never reaches 0. Equation (2) shows the kernel model.

$$w_{ij} = exp(-d_{ij}^2/\theta^2) \tag{2}$$

It is defined that i is the regression point index, j is the locational index, w_{ij} is the weight value of observation at location j for estimating the coefficient at location i, d_{ij} is the Euclidean distance between i and j, and θ is a fixed bandwidth size defined by a distance metric measure (Fotheringham et al., 2003).

The last stage in this study is conducted spatial cluster mapping, using the local indicator of spatial association (LISA). Spatial autocorrelation analysis calculates the Moran's I index which identifies areas that are significantly clustered or outliers. The process of computing and generating maps is conducted by using GeoDa™ software, which was developed by Luc Anselin as one of the developers of the concept of the dynamic of spatial data (Anselin, 2005). The theoretical base of Moran's I Model is that this model considers the effect of a spatial weight matrix as in the Pearson statistic (Anselin and Rey, 2010).

The collected data is then also visualized further by generating heatmaps for the health care facilities distribution and calculating the nearest average distance for each area to the facilities using QGIS. Further analysis is done using Geoda to create the cluster map and Moran's I scatter plot. Mapping of the social patterns is done for health care facilities located in the Special Capital Region of Jakarta only because there were limitations in the data collection process. The demographical data used for the variables: gender ratio, percentage of the population without an education, population count, and the ratio of the population within the working age.

3. RESULT AND DISCUSSION

3.1 Kernel Density Estimation (KDE) Map

In this study, the health care facilities (HCF) were divided into 2 categories, namely public health centers (PHC) and accredited hospitals. PHC has very limited capacity and types of services. Each stage of the analysis conducted in this research is divided into HCF in general, and for each category.

Figure 4 shows a density map for the distribution of health facility locations that was generated using the Kernel Density Estimation (KDE) technique. This technique is a part of various point pattern analyses to identify the main phenomenon, namely whether the pattern of the data set is clustering or dispersion (Fotheringham, Brunsdon, and Chalrton, 2000). The study area of this method is the Greater Jakarta Area. The KDE maps are in raster format which is generated from the value of smoothed density of the distribution of health facility locations across the study area. The kernel-based intensity estimation is influenced by determining the optimal bandwidth, which is determined by the amount of data and the standard distance from the location data (Fotheringham, Brunsdon, and Chalrton, 2000; Blackburn *et al.*, 2014).

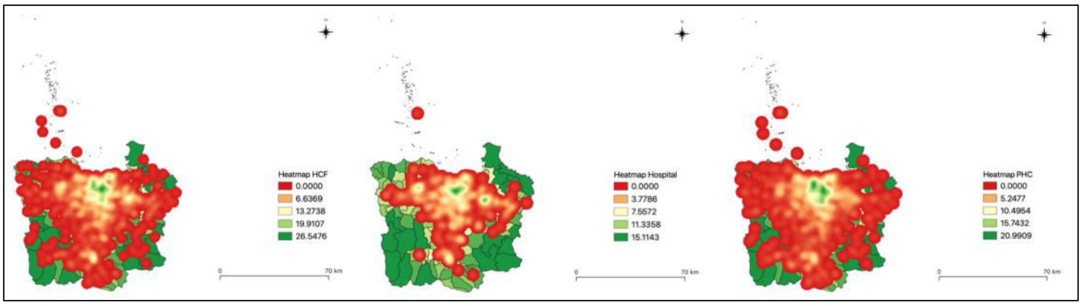

Figure 4. Health care facilities distribution heatmap

The standard distance value is calculated using the Spatial Point Pattern Analysis tool in the QGIS Processing Toolbox. The KDE maps are generated using the QGIS HeatMap Plugin, after optimal bandwidth calculation. The KDE maps in Figure 4 show some areas in the Greater Jakarta Area that lack health care facilities, especially for the hospital category (but we can see that these areas have a small population). Therefore, these maps indicate the relationship between the high density of health facilities and the population. For example, there are some areas with a high density of health facilities (up to around 20 PHC, or 15 hospitals, or 26 PHC and hospitals) while there are also areas that are not within the coverage at all of these facilities. Further analysis needs to be conducted to identify more specifically which areas require improvement in the availability of health facilities.

Further visualization is generated to observe the nearest average distance for each district to one of the health care facilities available to them. Figure 5 shows the nearest average distance visualization which was also generated using QGIS software. The visualization shows the average nearest distance for each region to the nearest health care facilities available within the area. The values are in meters and visualize the distance within an interval, from the shortest (represented in green) to the farthest (represented in red). This visualization further supports the idea that there might be a relationship between population and health care facilities distribution, this is shown from how the areas which have a high population (represented in the color red) mostly have a shorter average distance to health care facilities compared to areas which have a low number of population.

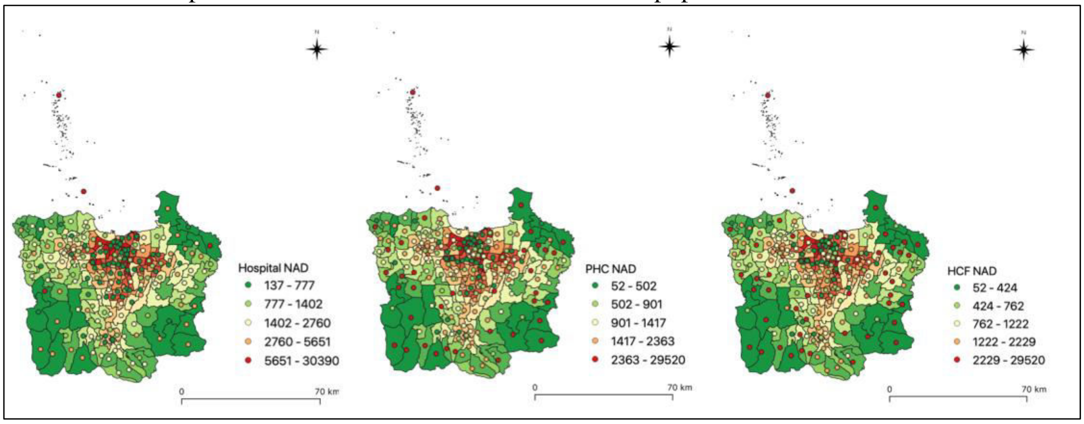

Figure 5. Health care facilities nearest average distance visualization

3.2 Geographically Weighted Regression (GWR)

The study area of this method is only within the Special Capital Region of Jakarta instead of the Greater Jakarta Area. This is due to limited data availability for several districts on the borderland of metropolitan Jakarta. At this stage of the study, the analysis result aims to examine the relationship between several socio-demographic variables on the number of health facilities in each sub-district. Socio-demographical characteristics are taken into account because health care accessibility is also directly related to predisposing demographical and social factors like age, gender, marital status, and education (R. Andersen & Newman, 2005; Cabrera-Barona et al., 2017). The variables taken into account in the study are the male/female gender ratio (X1), percentage of the population without an education (X2), population (X3), and the ratio of the population within the working age (X4).

The global regression conducted the goodness of fit test which will return the R^2 value. R^2 is a statistic that explains the variance accounted for within a relationship between variables. The value ranges from 0 to 1, in which when the value is 0 it indicates that the model does not explain any variability, and an R^2 value larger than 0.5 is usually considered a significant relationship (Salkind, 2010). The result of the global regression can be seen in Table 1. The result suggests that for the distribution of all health care facilities (HCF) and the distribution of public health centers (PHC), the relationship is relatively significant, but not for the distribution of hospitals within the area.

Table 1. Global Regression Result

Metrics	All HCF	Hospital	PHC
R^2	0.609	0.235	0.684
Adjusted R^2	0.569	0.157	0.651

The model will then calculate the weight and p-value of the distribution of health care facilities, hospitals, and public health centers across the studied area. The summary of the GWR result of each variable can be seen in Table 2-4.

The result suggests that for the distribution of all health care facilities the demographical variable that has the most significant relationship is the population count (X3), followed by the gender ratio (X1), and the ratio of the population within the working-age (X4). The result suggests that the percentage of the population without an education (X2) in an area does not have any significant relationship with the distribution of health care facilities in the area. For the distribution of hospitals, the demographical variable that has a significant relationship is the population count (X2). The result suggests that the gender ratio (X1), percentage of the population without an education (X2), and the ratio of the population within the working age (X4) do not have any significant relationship with the distribution of hospitals in the Greater Jakarta Area. For the distribution of public health centers, the demographical variable that has the most significant relationship is the population count (X3), followed by the gender ratio (X1), and the ratio of the population within the working-age (X4). The result suggests that the percentage of the population without an education (X2) in an area does not have any significant relationship with the distribution of health care facilities in the area.

The variable that appears to have significance across all measurements – be it all health care facilities, hospitals, and public health centers – is the population count (X3), which further supports the existence of a significant relationship between population count and the distribution of health care facilities.

Table 2. GWR All Health Care Facilities Summary

Metrics	β intercept	β X1	β X2	β X3	β X4	p intercept	p X1	p X2	p X3	p X4
Q1	0.000	-0.228	-0.056	0.730	0.236	0.996	0.053	0.631	0.000	0.028
Median	0.000	-0.228	-0.056	0.730	0.236	0.997	0.053	0.631	0.000	0.028
Q3	0.000	-0.228	-0.055	0.730	0.236	0.997	0.053	0.632	0.000	0.028
Min	0.000	-0.228	-0.057	0.730	0.236	0.996	0.053	0.621	0.000	0.028
Max	0.001	-0.228	-0.055	0.732	0.236	0.997	0.053	0.634	0.000	0.028
Average	0.000	-0.228	-0.056	0.730	0.236	0.997	0.053	0.631	0.000	0.028
IQR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.000	0.000
Global	-0.000	-0.228	-0.057	0.731	0.236	1.000	0.046	0.623	0.000	0.023

Table 3. GWR Hospital Summary

Metrics	β intercept	β X1	β X2	β X3	β X4	p intercept	p X1	p X2	p X3	p X4
Q1	0.000	-0.198	-0.244	0.345	0.154	0.998	0.224	0.137	0.027	0.292
Median	0.000	-0.198	-0.244	0.345	0.154	0.998	0.224	0.138	0.027	0.293
Q3	0.000	-0.198	-0.244	0.345	0.155	0.999	0.224	0.138	0.028	0.293
Min	0.000	-0.198	-0.244	0.343	0.154	0.996	0.224	0.137	0.027	0.286
Max	0.001	-0.197	-0.240	0.345	0.157	0.999	0.225	0.143	0.028	0.294
Average	0.000	-0.198	-0.244	0.345	0.155	0.998	0.224	0.138	0.028	0.293
IQR	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.001	0.000	0.001
Global	-0.000	-0.198	-0.242	0.344	0.154	1.000	0.217	0.132	0.023	0.288

Table 4. GWR Public Health Centre Summary

Metrics	β intercept	β X1	β X2	β X3	β X4	p intercept	p X1	p X2	p X3	p X4
Q1	0.001	-0.170	0.110	0.767	0.214	0.992	0.106	0.290	0.000	0.026
Median	0.001	-0.170	0.111	0.768	0.215	0.993	0.106	0.292	0.000	0.026
Q3	0.001	-0.170	0.111	0.768	0.215	0.993	0.106	0.293	0.000	0.026
Min	0.000	-0.170	0.105	0.767	0.213	0.991	0.106	0.288	0.000	0.026
Max	0.001	-0.170	0.111	0.771	0.215	0.998	0.106	0.314	0.000	0.027
Average	0.001	-0.170	0.110	0.768	0.215	0.993	0.106	0.292	0.000	0.026
IQR	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.002	0.000	0.000
Global	-0.000	-0.170	0.108	0.769	0.215	1.000	0.099	0.296	0.000	0.021

3.3 Local Indicator of Spatial Association (LISA)

The data is then processed to find the weight matrix. The spatial association test takes into account the population density of each area as the main variable which will be used to create the weight matrix. The variable was used to observe the relationship of health care distribution and population density within the studied area as previous analysis using GWR proved that this demographic variable has the most significant relationship throughout all categories. This is also especially important because health care accessibility itself varies across space. After all, both health care professionals and the population are not uniformly distributed (Ursulica, 2016; Wang & Luo, 2005).

The spatial contiguity matrix can be classified into 3: rook (in which two regions can be considered as neighbors if each is adjacent partly to each other on a boundary), bishop (in which two regions can be considered as neighbors if they meet at one point/vertex), and queen (a combination of the rook and bishop contiguities, in which two regions can be considered as neighbors if they share any part of the general restrictions) (Utomo, *et al*., 2013; Mathur, 2015). The visualization of the number of neighbors for each district can be found in Figure 6.

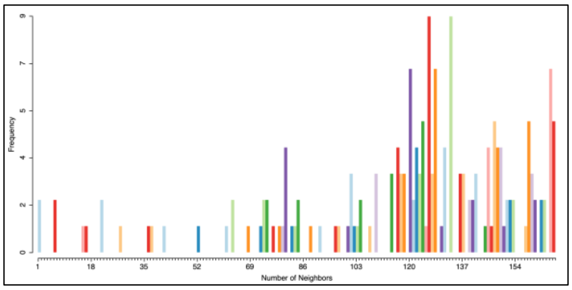

Figure 6. Weight matrix: number of neighbors for each district

Spatial autocorrelation analysis is a process of observing the existence of spatial clustering within a region. It aims to observe differences and similarities within the locations within the studied area. One of the most widely used tools for spatial global autocorrelation analysis is Moran's I tool which serves as an inferential statistic tool. The result of the analysis is interpreted within the context of the null hypothesis, in which the attribute being analyzed is randomly distributed within the study area (Mathur, 2015). Spatial autocorrelation can also be measured locally to evaluate the autocorrelation within local neighborhoods. It captures the local spatial variation and dependency while global measurements capture only one set of values that represents the autocorrelation across the study area (Mueller-Warrant et al., 2008). The summary of the Moran's I value can be seen in Table 5 and the result of the scatter plot and cluster map can be seen in Figure 7-9.

Table 5. Moran's I Index Value Summary

Variable	Moran's I Index
All Health Care Facilities	0.297
Hospitals	0.229
Public Health Centres	0.254

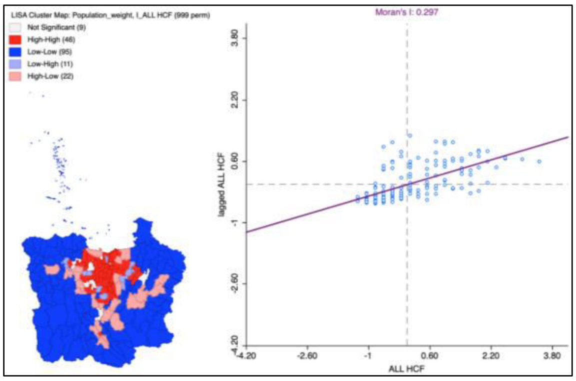

Figure 7. LISA Cluster Map and Moran's I Scatter Plot for all health care facilities in Greater Jakarta Area

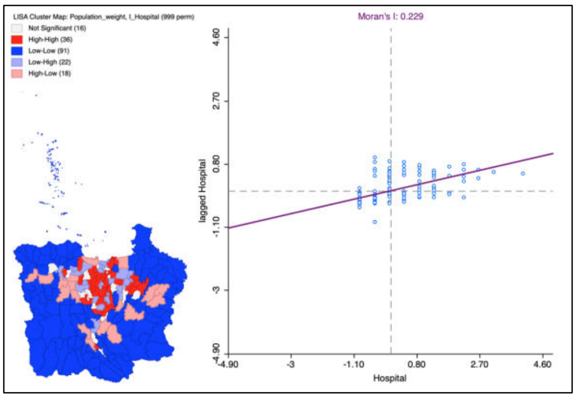

Figure 8. LISA Cluster Map and Moran's I Scatter Plot for hospitals in Greater Jakarta Area

Local Indicator of Spatial Association (LISA) is used to observe the extent of significant spatial clustering in which 5 scenarios may emerge: locations with high value with similar neighbors (high-high or hotspots), locations with low values with similar neighbors (low-low or cold spots), locations with high value with low-value neighbors (high-low or potential outliers), locations with low values with high-value neighbors (low-high or potential outliers), and locations with no significant local autocorrelation (Anselin, 1995). The result shows that there are spatial clusters within the studied area (with the Moran's I index being a positive value in all cases). The relationship between the distribution of health care facilities and the population is also highlighted within the result of the LISA Cluster Map, in which the red regions (high-high) are located within the center of the studied area, while the blue regions (low-low) are located in the peripheral areas. It is also shown that there are some outliers within the studied area, in which there are a high number population but a low number of health care facilities observed within the area and some areas with a relatively high number of health care facilities but a lower number of population. This indicates that even when there is an observed relationship between the population density of an area and the number of health care facilities observed within which indicates spatial clustering, there are still areas that need improvement in terms of the equal distribution of health care facilities based on the population distribution to further support equal access to health care.

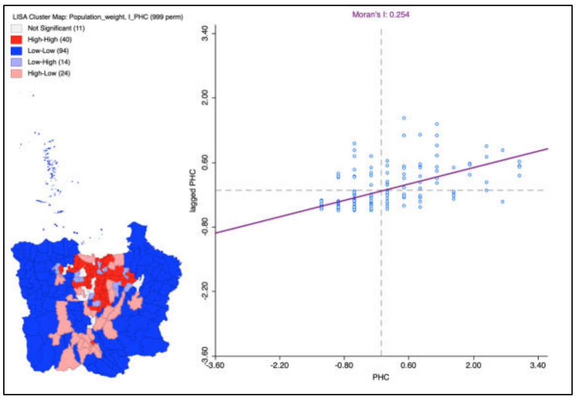

Figure 9. LISA Cluster Map and Moran's I Scatter Plot for public health centers in Greater Jakarta Area

4. CONCLUSION AND RECOMMENDATION

The result of this study suggests that the demographic variable that has the most significant relationship with the distribution of health care facilities is the population. This is proved by the analysis result based on Geographically Weighted Regression which was used to observe how several demographical variables, namely the gender ratio, percentage of the population without an education, population, and the ratio of the population within the working-age affect the distribution of the health care facilities within the Special Capital Region of Jakarta. The result of the analysis supports the relationship between health care distribution within a certain area with its population but also observed a relatively significant relationship with gender ratio and the ratio of the population within the working age in the distribution of public health centers and health care facilities in general. Further analysis was conducted to discover the existence of spatial clustering of the distribution of health care facilities within the Greater Jakarta Area. The data was analyzed using Moran's I to find that there are spatial clusters within the studied area. The study found that spatial clustering exists within the studied area, but there are also some outliers – in which there are a high number population but a low number of health care facilities observed within the area and some areas with a relatively high number of health care facilities but a lower number of population – which indicates that even when there is an observed relationship between the population density of an area and the number of health care facilities observed within which indicates spatial clustering, there are still areas that need improvement in terms of the equal distribution of health care facilities to further support equal access to health care.

This study contributes to evaluating the availability of health facilities, not only in the city of Jakarta but also in surrounding cities. Jakarta as the only megacity in Indonesia, of course, has a complete network of service providers, including health services. But what about the surrounding area? The unavailability of health facilities or health facilities with complete services will encourage people in the suburbs to access hospitals in the city center, which are far from their homes. This condition will certainly cause problems, especially during the pandemic, because in addition to making it difficult for sick residents to reach the hospital to be served, it also limits the capacity of the hospital to serve the surrounding community.

There are several limitations in this study, including the completeness of socio-demographic data from all cities/districts studied. The completeness of the data allows for further studies of various variables that affect the social demographic characteristics of the community. Hence, further studies should be conducted to explore the relationships to the health care facilities distribution within the Greater Jakarta Area. Regarding accessibility to health facilities, this study only analyzed the proximity of health facilities to the residences of the community. Further analysis is needed on the availability of public transportation facilities that are very likely to be needed by the community to reach health facilities, especially to the hospital.

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