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GIS Modeling for Economic Agglomeration/ Cluster of Gross Regional Domestic Product (GRDP) Data Using Moran's I Analysis: A Case Study Jakarta, Indonesia

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Abstract. The Gross Regional Domestic Product (GRDP) is a statistical indicator utilized to quantify the economic magnitude of a certain region. Urban economies are crucial in driving national growth, particularly in developing nations where urbanization is advancing rapidly. Jakarta, Indonesia, exemplifies an urban economy with substantial influence over national economic patterns. This study aims further to understand the spatial patterns of economic activity in Jakarta using Geographic Information Systems (GIS) and Moran's I Analysis of Gross Regional Domestic Product (GRDP) data. Prior studies have frequently overlooked the spatial dimensions of economic agglomeration, which are crucial for thorough urban planning and policy formulation. This research aims to address the lack of understanding regarding the formation and impact of economic clusters on urban economic growth by explicitly examining Jakarta. The study utilizes spatial autocorrelation techniques to detect and examine economic clustering and agglomeration patterns. In addition, the authors discuss the Gross Regional Domestic Product (GRDP) statistics for 2022, obtained from the Statistical Agency of Jakarta. This data offers a thorough overview of the economic performance in different districts. The spatial autocorrelation/ Moran's I results revealed notable concentrations of economic activity in central and north Jakarta, which suggest regions with substantial economic production and prospects for future expansion. These clusters exhibit concentrations of commercial and industrial activities, indicating specific opportunities for policy intervention to promote economic development. The study highlights the importance of analysis for urban planners and policymakers, providing a detailed insight into the economic landscape of city areas and guiding holistic economic planning.

Keywords: GRDP, Economic Agglomeration, GIS, Moran's I Analysis, Spatial Autocorrelation, Jakarta.

Introduction

Identifying economic activity clusters and analyzing their geographical representation are crucial but complex tasks in comprehending urban and regional development (Yang et al., 2012). Contemporary economic growth is predicated upon the principles of innovation, scientific advancements, and the cultivation of novel economic sectors predominantly focused inside urban centers (Kosareva and Polidi, 2017). The economic sector is a fundamental factor that consistently influences the progress and growth of a particular region (Paun et al., 2019). In order to assess the economic dimensions of urban areas, economists may employ Gross Domestic Product (GDP) as a metric to gauge the magnitude of urban economic expansion. The Gross Domestic Product (GDP) is often regarded as a reliable measure for assessing the economic state of a nation (Hasan et al., 2022). The growth of the

Gross Domestic Product (GDP) has the potential to generate a surge in the demand for urban land, consequently resulting in a subsequent increase in land values and property prices (Ong Tze San, 2013). This phenomenon is most conspicuous in urban areas experiencing rapid growth, characterized by a scarcity of land resources and subsequent intensification of spatial competition, resulting in escalated land prices (Balchin et al., 1995). According to Athreye, 2012; Figueras et al. (2021), a significant interconnection exists between Gross Domestic Product (GDP) and agglomeration. Agglomeration refers to the spatial concentration of economic activities within specific geographic regions and can potentially result in heightened productivity and economic expansion (McCann and Van Oort, 2019). Cities with a higher GDP tend to attract more businesses and individuals because they provide more opportunities and amenities. This can lead to further agglomeration as more economic activities are concentrated in these locations with high GDPs (OECD, 2008).

The predominant field of research pertaining to Gross Domestic Product (GDP) mostly centers on measurement and calculation (Alexander et al., 2017; Dynan and Sheiner, 2018), economic growth (Özyılmaz, 2022; Roemer and Gugerty, 1997), macroeconomy policy (Kurpayanidi et al., 2021; Taylor, 2000), income inequality (Dabla-Norris et al., 2015; Halmos, 2011), demographic changes (Arnott and Chaves, 2012; Kim and others, 2016). The correlation between GDP and geography is inherent and inseparable since it indicates regional differences, economic specialization, and the urban-rural split (Esposti and Bussoletti, 2008). Hence, the current body of research pertaining to spatial distribution remains constrained, prompting the authors to address this concern by conducting an analysis of GDP data, specifically focusing on GDP's Jakarta within the context of spatial analysis. This study aims to analyze the agglomeration or cluster formed by GDP data as an indicator for assessing economic growth. The author analyses the spatial distribution of GDP data in order to ascertain the existence of spatial patterns, clusters, and agglomerations that are indicative of urban economic growth.

In the modern era, the technology of spatial planning has been increasing widely, and one of the popular technologies that planners or designers commonly use is Geographic Information System (GIS). A classic definition of GIS is that a Geographic Information System (GIS) is a computerized database management system for collecting, storing, analyzing, and displaying geographically referenced data for decision-making and research purposes. In general, a GIS consists of five interdependent components, including technology, software, data, procedures, and people, that assist in creating maps (Law, M., & Collins, A., 2016). Furthermore, the author of this study also employs a border operation as a first step in creating the subsequent analysis using ArcGIS capabilities. The authors adopt spatial autocorrelation analysis (Moran's I Analysis) within a Geographic Information System (GIS) tool to ascertain a spatial pattern or cluster indicative of agglomeration in Jakarta. Geographical autocorrelation analysis uses Moran's I statistic to assess the level of correlation within a given geographical extent (Wang et al., 2023). Therefore, using spatial autocorrelation analysis, the study addresses two primary inquiries: Is there any evidence of spatial clustering of Gross Regional Domestic Product (GRDP) per district? Secondly, what is the scope of these spatial clusters?

Jakarta, the dynamic capital city of Indonesia, is a thriving urban center that serves as the central hub for the country's economic, political, and cultural domains (Rusiawan et al., 2015). The Gross Regional Domestic Product (GRDP) is a pivotal indicator for comprehending the economic importance of Jakarta (Putri Yunita et al., 2021). The authors utilize the spatial analysis context to examine economic growth by employing GRDP data to analyze the agglomeration/cluster in Jakarta as a crucial factor in the Indonesian economy. The outcome will ascertain the effect of Jakarta's Gross Regional Domestic Product (GRDP) as an indicator of economic growth on spatial clustering and agglomeration.

Literatures Review

Gross Regional Domestic Product (GRDP)

Gross Regional Domestic Product (GRDP) refers to the aggregate value of products and services generated within a certain geographic region, typically a county or city, over a designated period, typically one year (Angela, 2021; Dewi et al., 2021). The term "domestic" refers to activities, issues, or phenomena that are related to The Gross Regional Domestic Product (GRDP) and directly influence the creation of income within a certain area (Sutrasna and Duha, 2023). The Gross Regional Domestic Product (GRDP) quantifies the aggregate economic production and revenue produced within a particular geographic area, indicating that region's financial well-being and efficiency. This metric is of the greatest significance in understanding the economic performance of various areas within a nation, as it offers a comprehensive study of the economic contribution of each region to the overall economy (Fraumeni, 2022).

The rise in Gross Regional Domestic Product (GRDP) is anticipated to generate additional government revenue, which can be allocated towards funding government programs and the development of facilities and infrastructure (Suhartono, 2020). This allocation aims to enhance community services, thereby potentially boosting productivity levels. Economic growth is typically quantified by the Gross Regional Domestic Product (GRDP) value at constant prices (Ai and Wardoyo, 2015). Examining economic growth using Gross Regional Domestic Product (GRDP) at constant prices provides insight into the specific sectors of the regional economy that are increasing and contributing to this growth (Darma, 2020). It has the ability to detect patterns in efficiency, alterations in industrial or service sector production, and movements in consumer behavior (Chamberlin, 2010). In addition, comparing the GRDP at constant prices across different regions or over different periods can provide insights into regional economic disparities, growth patterns, and the effectiveness of regional economic policies (Jurun and Pivac, 2011). This approach is preferable because it allows for an assessment of economic changes that are not influenced by fluctuations in prices. By using constant prices, the resulting change in GRDP reflects a real shift in economic output unaffected by price variations (Lyu et al., 2018). Furthermore, the Gross Regional Domestic Product (GRDP) is essential for policymakers and economists. It aids in determining the industries that are fueling economic expansion in a certain region and highlighting the ones that require further assistance or investment (Saudi et al., 2021).

Economics of Agglomeration

The concept of economies of agglomeration pertains to the advantages that come from the spatial concentration of enterprises and individuals within urban areas and industrial clusters (Abdel-Rahman, 1990; Glaeser, 2010). The concept emphasizes that several benefits become visible when companies and their personnel are situated nearby, either in highly populated metropolitan areas or specialized industrial clusters (Song et al., 2012). These advantages extend beyond the evident logistical benefits of proximity between enterprises and their employees (Giuliano et al., 2019). They also encompass more subtle features such as the facilitation of idea sharing, the swift dissemination of innovation, and the creation of a talented and specialized workforce (Cooke, 2007). These benefits play a crucial role in these regions' economic strength and competitive advantage, stimulating creativity, promoting a strong labor market, and improving the general well-being of those living and working in these successful economic centers (Arauzo-Carod and Viladecans-marsal, 2006). The aforementioned advantages are derived mainly from the reduction in transportation costs, encompassing the challenges associated with the exchange of products, individuals, and concepts (Thisse, 2019).

The classification of agglomeration economies has three primary types, namely urbanization economies, industrialization economies, and localization economies (Abdel-Rahman, 1990). Agglomeration economies play a crucial role in facilitating the flow of ideas, leading to innovation and advancements in enterprises' production processes. This, in turn, results in increased productivity and subsequent capital accumulation within urban areas (Duranton and Kerr, 2018). Agglomeration economies contribute to increased productivity, facilitating enterprises' accelerated growth and fostering both the physical and economic expansion of urban areas (Fujita and Thisse, 1996). A significant interconnection exists between Gross Domestic Product (GDP) and agglomeration economies inside metropolitan regions. This relationship is characterized by a mutual influence, wherein the amount of economic activity and production (GDP) in a particular location may both impact and be impacted by agglomeration effects (Sbergami, 2002).

An increase in the gross domestic product (GDP) has the potential to foster greater levels of urbanization and industrialization, hence generating further agglomeration economies (Turok and McGranahan, 2013). This association suggests that an increase in a nation's or region's GDP frequently results in a significant rise in urban development and industrial activity (Kalimeris et al., 2020). With the growth of GDP, which indicates a strong economy, there is an increase in resources that may be allocated towards investing in urban infrastructure, industrial projects, and technical breakthroughs (Gylfason and Zoega, 2006). The injection of funds and resources into urban and industrial sectors catalyzes more growth, enticing firms, investors, and qualified workforce to these regions (Esposti and Bussoletti, 2008). Agglomeration economies are characterized by the concentration of firms and expertise in specific locations, which results in increased efficiency, innovation, and production (Athreye, 2012). In return, these economies attract more enterprises and persons, thereby establishing a positive cycle of growth and development (Economides et al., 2020).

Spatial Analysis of Agglomeration

The application of spatial analysis in examining agglomeration phenomena has been extensively employed in the investigation of various subject matters. It tries to figure out what causes agglomeration, what effects it has, and how agglomeration processes change over time and space. Arbia and Baltagi (2008) provide an explanation of a spatial analysis technique known as spatial econometrics. This approach combines spatial statistics with econometrics to model spatial relationships between economic variables. The techniques employed include spatial autocorrelation, spatial heterogeneity, spatial lag, spatial error models, and spatial regression diagnostics (Arbia and Baltagi, 2008). There are many studies that exist for measuring the spatial concentration of activities, such as integrating the study of large-scale industrial clustering with the use of Kernel Density analysis along with Spatial Autocorrelation (Lu and Cao, 2019), the geographical patterns of agglomeration at both global and local scales (Guillain and Gallo, 2010), Kernel Density and global and Local Moran's I analysis (Cheruiyot, 2022). The analysis of spatial agglomeration involves a range of essential functions: identifying Spatial Structure (Zhu et al., 2021), the comprehension of structures of networks (Zhao et al., 2021), developmental dynamics of intercity relationships (Hong et al., 2021).

The present research attempts to assess the significance of clusters through spatial autocorrelation analysis within a certain region and examine their spatial distribution. Spatial autocorrelation refers to the phenomenon wherein there is a concurrence between the similarity of values and the similarity of locations (Anselin, 2000). This implies that the value of a variable at a certain place is not random but rather expected to be comparable to values of the same variable at neighboring locations. Spatial autocorrelation can exhibit either positive or negative values. Positive spatial autocorrelation refers to the phenomenon where comparable values tend to cluster together in certain geographic locations, whereas negative spatial autocorrelation arises when dissimilar values are found near each other (Gallo and Ertur, 2005). Understanding and recognizing spatial autocorrelation is essential for precise spatial analysis and modeling. This has an impact on the methods of data collection, analysis, and interpretation in diverse domains such as geography, ecology, economics, and urban planning.

In order to accomplish this objective, the research utilizes Moran's I analysis, a statistical technique commonly employed in spatial statistics for the identification of spatial autocorrelation (Odland, 2020). Moran's I analysis is a statistical technique specifically developed to quantify and detect the existence of spatial autocorrelation in data (Anselin, 2000). This approach aims to uncover patterns of cluster distribution and offer valuable insights into the spatial dynamics of the region being examined. The Moran's I analysis involves comparing the value of a variable at a specific site with the values of the same variable at nearby locations. The basic idea of this study is to determine if there is a consistent pattern in the spatial distribution of the variable, as opposed to random dispersion. Integrating Moran's I analysis into research improves comprehension of spatial patterns and linkages within the data, especially in economic agglomeration.

Datasets and Methods

Study Area

This study was conducted in the DKI Jakarta, the capital of Indonesia, which is a dynamic metropolis that has significant influence in terms of its economic, political, and cultural impact (Badan Pusat Statistik Provinsi DKI Jakarta, 2023). Administratively, DKI Jakarta is geographically divided into six regions, encompassing 44 districts and 267 sub-districts. According to the Statistic Agency of Indonesia/ Badan Pusat Statistik Provinsi DKI Jakarta (2023), the total area of DKI Jakarta is 7,660 square kilometers, consisting of a land area of 662.33 square kilometers and a marine area of 6,977.5 square kilometers. Moreover, the population density is significantly increased. In 2023, the population was recorded to surpass 10 million people, with a population density ranging from 15,978 to 20,360 residents per square kilometer.

In order to examine the spatial distribution of agglomeration or clustering, the author utilizes a case study conducted in the Jakarta Region, focusing on the boundaries of 44 districts within six regions. This case study shows the spatial context of the Gross Regional Domestic Product (GRDP) data. Figure 1 depicts the spatial boundary of Jakarta across 44 district administrations.

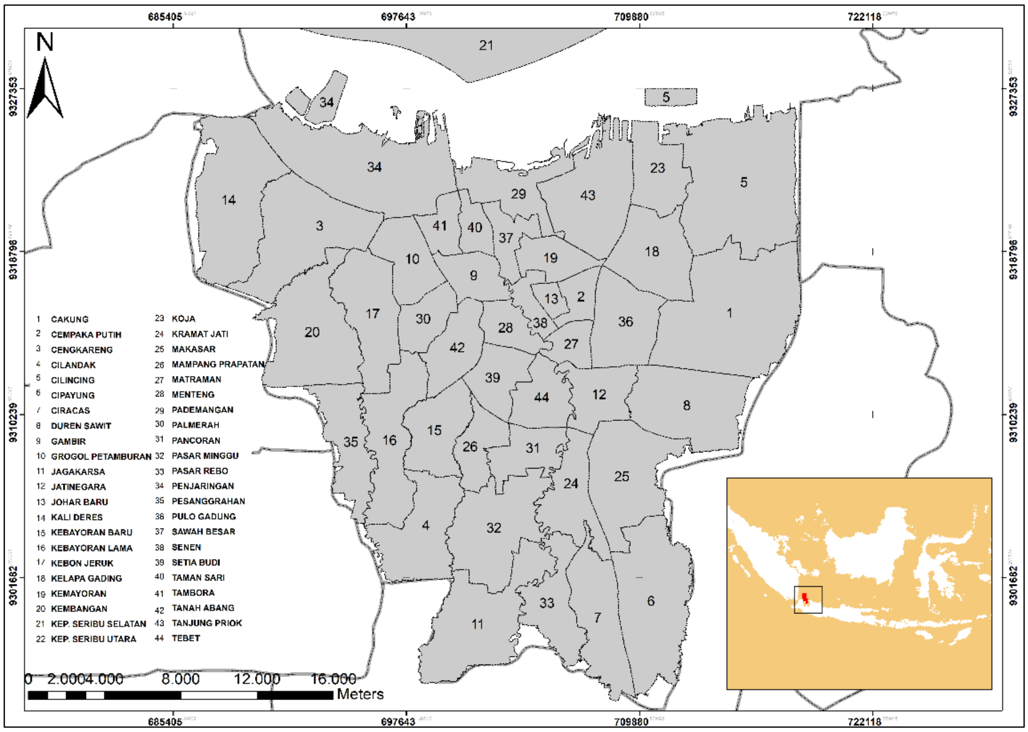


Fig. 1. Map of 44 districts of Jakarta (Jakarta Government, 2020).

Data

The present study used Moran's I analysis to examine economic agglomeration through the analysis of district-level GDP/GRDP data. The secondary data utilized, as shown in Table 1, is sourced from the statistical agency of Jakarta (Badan Pusat Statistik, BPS), which may be accessed openly through the official government websites https://jakarta.bps.go.id/publication.html. The details regarding the boundaries of Jakarta can be seen on the official website, which provides comprehensive information at https://jakartasatu.jakarta.go.id/portal/apps/sites/#/public. Both of these websites are free from copyright restrictions.

Table 1. Data Sources Used in This Study.

No.	Data	Description	Year	Sources
1	Jakarta's Boundary (Shapefile.shp)	The physical administrative boundaries by district and regency	2022	Web-GIS of Jakarta
2	Gross Regional Domestic Product (GRDP) at 2010 Constant Price	GDP used in this study is per region (GRDP) in DKI Jakarta (44 Districts in 6 Regions)	2022	Statistic Agency of Jakarta (BPS)
3	Data Vector of GRDP (Shapefile.shp)	GRDP data converted into vector data	2022	Analysis

The data vector of GRDP represents the conversion of Gross Regional Domestic Product (GRDP) data into a vector format, specifically utilizing shapefiles (.shp). By converting GRDP data into vector format, the study can perform spatial analysis. This involves mapping and analyzing economic data across different geographic regions, which in this case are the districts of DKI Jakarta.

Table 2 presents the data on the Gross Domestic Product (GDP) per region, namely the Gross Regional Domestic Product (GRDP), across six regions and 44 districts in Jakarta for the year 2022. The Gross Regional Domestic Product (GRDP) dataset comprises 44 districts in 2022. The Gross Domestic Product (GDP) of each district has been evaluated using constant price 2010 because the measurement of gross domestic product (GDP) at constant prices offers a more accurate depiction of a country's true level of economic expansion (Stahel, 2021).

Table 2. Gross Regional Domestic Product Data for 44 Districts of Jakarta at Constants Price, 2022 (Badan Pusat Statistik Provinsi DKI Jakarta, 2023).

No.	District	City	GRDP (Billion Rupiah)	Total (Billion Rupiah)	No.	District	City	GRDP (Billion Rupiah)	Total (Billion Rupiah)
1	Cengkareng	Jakarta Barat	43,210.73	345,685.84	23	Pasar Minggu	Jakarta Selatan	43,750.07	
2	Grogol Petamburan	Jakarta Barat	50,210.73		24	Pesanggrahan	Jakarta Selatan	45,176.55	
3	Kali Deres	Jakarta Barat	37,927.49		25	Setia Budi	Jakarta Selatan	50,659.78	
4	Kebon Jeruk	Jakarta Barat	35,593.87		26	Tebet	Jakarta Selatan	49,176.55	
5	Kembangan	Jakarta Barat	38,284.06		27	Cakung	Jakarta Timur	28,636.74	329,680.72
6	Palmerah	Jakarta Barat	47,599.69		28	Cipayung	Jakarta Timur	29,548.24	
7	Taman Sari	Jakarta Barat	45,194.93		29	Ciracas	Jakarta Timur	29,746.45	
8	Tambora	Jakarta Barat	47,664.34		30	Duren Sawit	Jakarta Timur	30,957.39	
9	Cempaka Putih	Jakarta Pusat	59,453.05	482,088.23	31	Jatinegara	Jakarta Timur	39,968.74	
10	Gambir	Jakarta Pusat	64,261.03		32	Kramat Jati	Jakarta Timur	38,634.10	
11	Johar Baru	Jakarta Pusat	57,679.23		33	Makasar	Jakarta Timur	28,937.64	
12	Kemayoran	Jakarta Pusat	59,883.46		34	Matraman	Jakarta Timur	38,719.38	
13	Menteng	Jakarta Pusat	58,721.12		35	Pasar Rebo	Jakarta Timur	29,794.95	
14	Sawah Besar	Jakarta Pusat	57,369.98		36	Pulo Gadung	Jakarta Timur	34,737.09	
15	Senen	Jakarta Pusat	61,959.55		37	Cilincing	Jakarta Utara	53,376.13	350,232.86
16	Tanah Abang	Jakarta Pusat	62,760.81		38	Kelapa Gading	Jakarta Utara	55,225.79	
17	Cilandak	Jakarta Selatan	41,134.69	451,765.49	39	Koja	Jakarta Utara	54,372.51	
18	Jagakarsa	Jakarta Selatan	40,275.55		40	Pademangan	Jakarta Utara	59,146.34	
19	Kebayoran Baru	Jakarta Selatan	44,681.06		41	Penjaringan	Jakarta Utara	62,739.95	
20	Kebayoran Lama	Jakarta Selatan	43,248.51		42	Tanjung Priok	Jakarta Utara	65,372.14	
21	Mampang Prapatan	Jakarta Selatan	47,989.45		43	Kep. Seribu Selatan	Kepulauan Seribu	2,095.93	3,591.86
22	Pancoran	Jakarta Selatan	45,673.28		44	Kep. Seribu Utara	Kepulauan Seribu	1,495.93	

Table 2 presents the comprehensive Gross Regional Domestic Product (GRDP) data, categorized into 17 distinct economic activities. According to Badan Pusat Statistik Provinsi DKI Jakarta (2023), these activities include Agriculture, Forestry, and Fishing; Mining and Quarrying; Manufacturing; Electricity and Gas; Water supply, Sewerage, Waste Management, and Remediation Activities; Construction; Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles; Transportation and Storage; Accommodation and Food Service Activities; Information and Communication; Financial and Insurance Activities; Real Estate Activities; Business Activities; Public Administration; Defence and Compulsory Social Security; Education; Human Health and Social Work Activities; and Other Services Activities.

Methods

The study develops a method of Moran's I analysis and provides a first thorough overview of the data through descriptive analysis (Fig.2).

Statistic Descriptive Analysis

Descriptive statistics are used to organize data by describing the connection between variables in a sample or population (Yellapu, 2018). Moreover, variables are quantifiable qualities that change over time or between persons and are the main focus of research studies (Larson, 2006). Measures of frequency (ratios, rates, proportions, and percentages), central tendency (mean, median, and mode), dispersion/variation (range, variance, and standard deviation), location (percentiles, deciles, and quartiles), and graphical techniques are included in descriptive statistics (Bartz, 1988; Ibe, 2014; Larson, 2006; Yellapu, 2018). Variables are classified into four types: nominal, ordinal, discrete, and continuous(Mishra et al., 2018). The first two are referred to as qualitative data, whereas the latter two are referred to as quantitative data (Mishra et al., 2018).

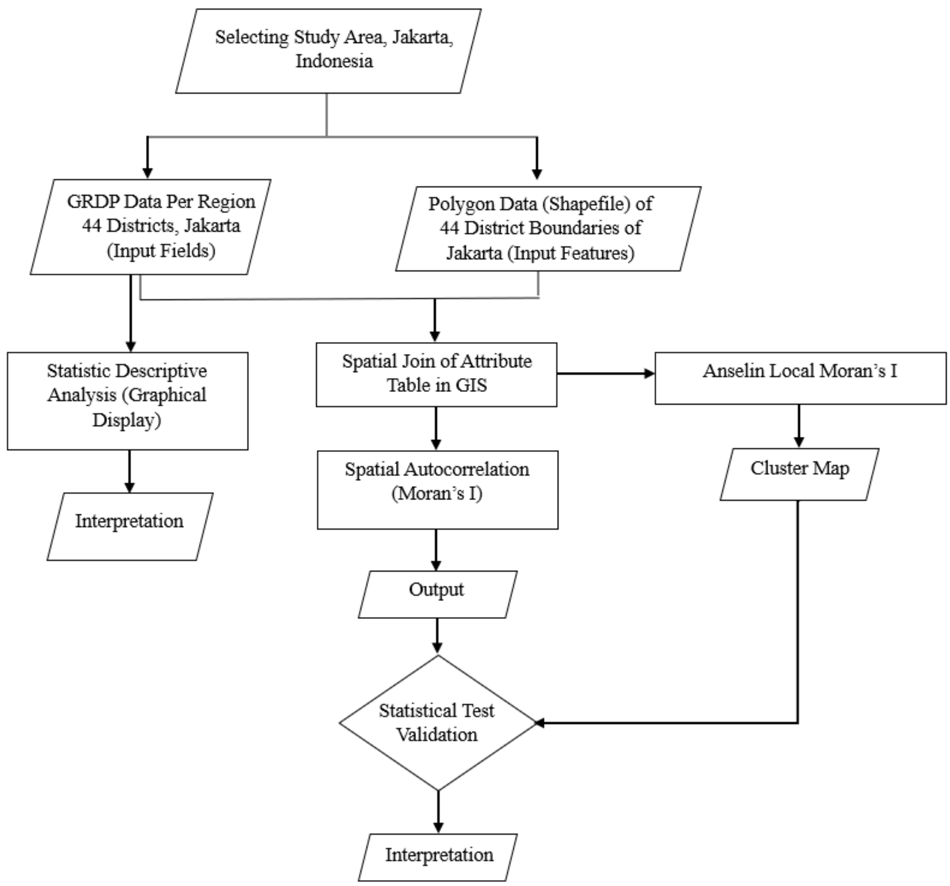


Fig. 2. Flowchart Analysis of the Research.

It is possible to conduct a descriptive statistical study to analyze spatial autocorrelation using Moran's I in a hypothetical dataset involving GRDP data per district in Jakarta inside a GIS framework. This analytical approach allows for the examination of the data's distribution and inherent properties, hence providing valuable insights. This study will mainly employ visual representations/ graphical displays and present a comprehensive overview of the fundamental aspects pertaining to variables inside a dataset, such as diagrams and charts, to facilitate comprehension of the GRDP data.

Spatial Autocorrelation (Moran's I)

The study develops spatial autocorrelation analysis, specifically employing Moran's I. The assessment of global spatial autocorrelation relies on the utilization of Moran's I statistic, which is widely recognized as the predominant tool for evaluating spatial clustering(Cli and Ord, 1973; Putra et al., 2020). Spatial autocorrelation quantifies the degree of closeness between different places and assesses the similarity of attributes associated with each site (Getis, 1995). Hence, positive spatial autocorrelation is observed when there is a tendency for high or low values of a random variable to exhibit spatial clustering, whereas negative spatial autocorrelation is observed when geographical areas tend to be surrounded by neighbors with significantly differing values (Gallo and Ertur, 2005). The Moran's index is mathematically defined by Equation (1) in the following manner:

$$Moran's\ I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} Wij\ (x_i - \overline{x})(x_j - \overline{x})}{S^2\ \sum_{i=1}^{n}\sum_{j=1}^{n} Wij}$$

Furthermore, the variable n represents the quantity of spatial units that are indexed by the variables *i* and *j*. The variable *x* is used to identify a specific variable. Additionally, $\overline{x}$ is the mean value of the variable *x*. Lastly, *Wij* is a matrix that contains the spatial weights associated with the spatial units *i* and *j* (Anselin, 2000; Putra et al., 2020).

Anselin Local Moran's I

A local spatial autocorrelation statistic called Local Moran's I is derived from the Moran's I statistic. It was created as a local indicator of spatial association, or LISA statistic, by Anselin in 1995 (Rey et al., 2023). The initial formulation of the Local Moran index, as established by (Anselin, 1995), can be expressed as:

$$I_i = \frac{x_i - \overline{x}}{S_i^2} \sum_{j=1, j\neq i}^{n} wi,j\ (x_j - \overline{x})$$

Let x_i represent an attribute for feature *i*, $\overline{x}$ denotes the mean of the associated attribute, and *wi,j* represents the spatial weight between features *i* and *j*, and:

$$S_i^2 = \frac{\sum_{j=1, j\neq i}^{n}(x_j - \overline{x})^2}{n-1}$$

S_i^2 is the variance of the variable x in the dataset, excluding the observation at position i. Let *n* represent the total number of features. S_i^2 quantifies the variability or dispersion of the attribute values around their mean in the spatial context, which is essential for identifying local patterns of spatial association (Anselin, 1995).

Table 3 outlines the results of Anselin Local Moran's I statistical test, which identifies spatial clusters and outliers based on the Gross Regional Domestic Product (GRDP) data. When the *p*-value is less than 0.05, the results are statistically significant. A positive Moran Index ($M > 0$) indicates high or low-value clusters (HH or LL) where similar values are grouped. Conversely, a negative Moran Index ($M < 0$) indicates spatial outliers (HL or LH), where high values are surrounded by low values or vice versa. This analysis helps in understanding the spatial distribution and clustering of economic activity across regions.

Statistical Significance Testing

The Global Moran's index, or Moran's I, is a statistical measure ranging between -1 and 1. A higher magnitude of the variable Moran's I signifies a greater degree of spatial correlations, whereas a value approaching zero indicates a lower level of autocorrelation. The autocorrelation test utilizes Moran's I test statistics to examine the following assumptions (Kondo, 2021; Wang et al., 2023).

- 0<Moran's I≤ 1; the spatial correlation is positive. As the value increases, the significance of the spatial correlation increases.
- Moran's I = 0; the spatial relationship is a state with random distribution.
- -1≤ Moran's I<0; the spatial connection has a negative correlation. The geographic correlation grows narrower as the value drops and the spatial disparity rises.

Table 3. Statistical Test of Anselin Local Moran's I.

p- value (ALMI_*p*)	Moran Index	Implication	Cluster Type
$p < 0.05$	$M > 0$	High or Low-Value Cluster	HH (High-High Cluster) or LL (Low-low Cluster)
$p < 0.05$	$M < 0$	Outlier	HL (high value is surrounded primarily by low values) or LH (low value is surrounded primarily by high values)

In an alternative approach, the utilization of a *p*-value can be employed to quantify the likelihood of observing a value that is as severe or even more extreme than the observed value, assuming the null hypothesis is true (Li et al., 2007; Tiefelsdorf and Boots, 1995). The null and alternative hypotheses employed in Moran's test are as follows.

- Null Hypothesis (H_0) : The data exhibits a random dispersion pattern.
- Alternative Hypothesis (H_1) : The data exhibits non-random dispersion, displaying discernible patterns of clustering.

If the *p*-value associated with Moran's I is below a specific significance level (α = .05), it is possible to reject the null hypothesis and decide that the data exhibits spatial clustering that is unlikely to be the result of random chance.

Results and Discussions

Statistic Descriptive (Graphical Display)

The analysis presents a dataset utilizing simple summary descriptive statistical measures to enhance readability and facilitate the reader's comprehension of the data, particularly in identifying Gross Regional Domestic Product types and characteristics in Jakarta.

The 2022 GDP of Jakarta, measured at constant prices in 2010, amounts to 1,953.45 trillion rupiah or 126.15 billion US dollars (Badan Pusat Statistik Provinsi DKI Jakarta, 2023). Jakarta is divided into six regions and 44 districts. The regions and districts in Jakarta are ranked in terms of their GDP/GRDP, with the Centre of Jakarta (Jakarta Pusat) having the highest, followed by South Jakarta (Jakarta Selatan), North Jakarta (Jakarta Utara), West Jakarta (Jakarta Barat), and East Jakarta (Jakarta Timur). On the other hand, Jakarta Island (Kepulauan Seribu) has the lowest GDP/GRDP.

Figure 3 displays the proportion of each district's contribution to the total GDP in 2022. The Central Jakarta districts (Gambir, Cempaka Putih, Senen, Johar Baru, Kemayoran, Sawah Besar, Menteng, Tanah Abang) have the highest average contribution to the gross regional domestic product (GRDP) of Jakarta, ranging from 2.9% to 3.3% (482 trillion rupiah). The districts in North Jakarta (Tanjung Periok, Penjaringan, Pademangan) are closely followed, with contributions ranging from 2.5% to 3.3%. In contrast, the Jakarta Islands (Kep. Seribu Selatan and Kep. Seribu Utara) have the smallest Gross Regional Domestic Product (GRDP) contribution to the overall Gross Domestic Product (GDP) of Jakarta, ranging from 0.08% to 0.11% or 3.59 trillion rupiah.

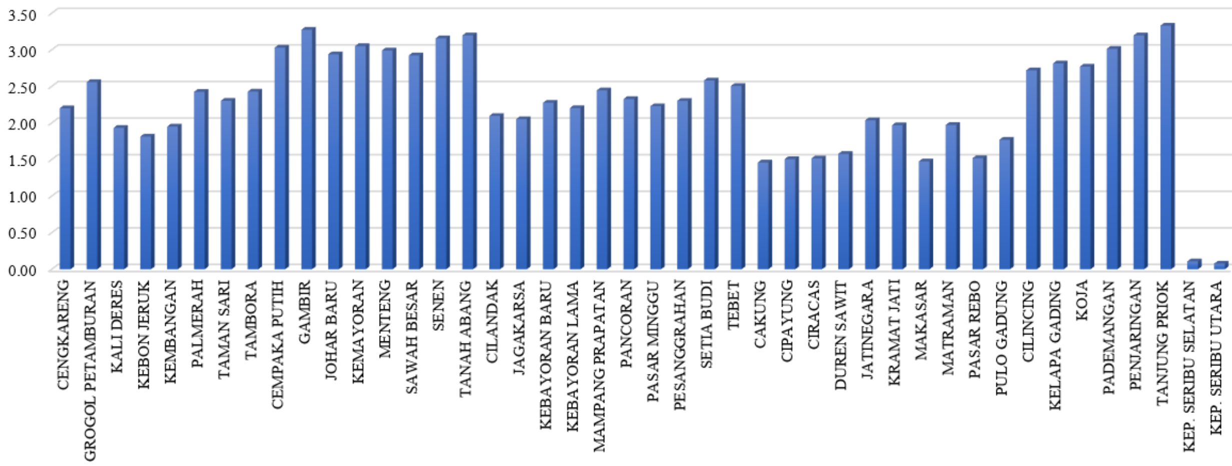


Fig. 3. The percent of each district's contribution to the overall Gross Regional Domestic Product (GRDP) in Jakarta, 2022.

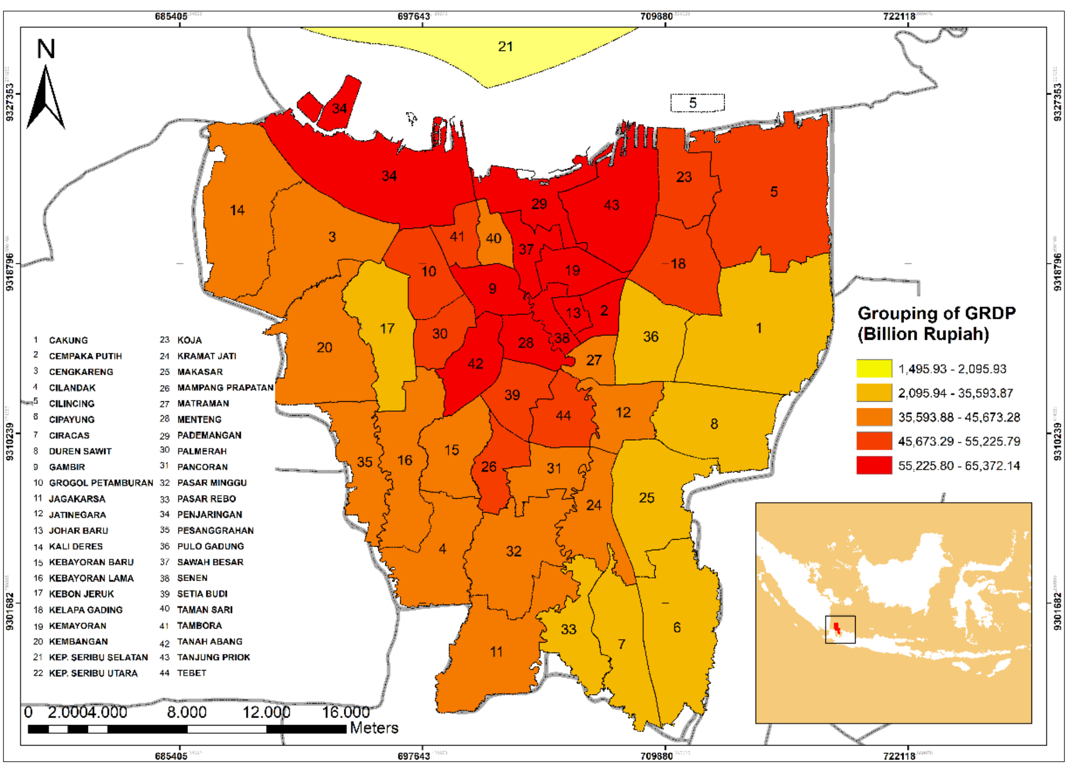


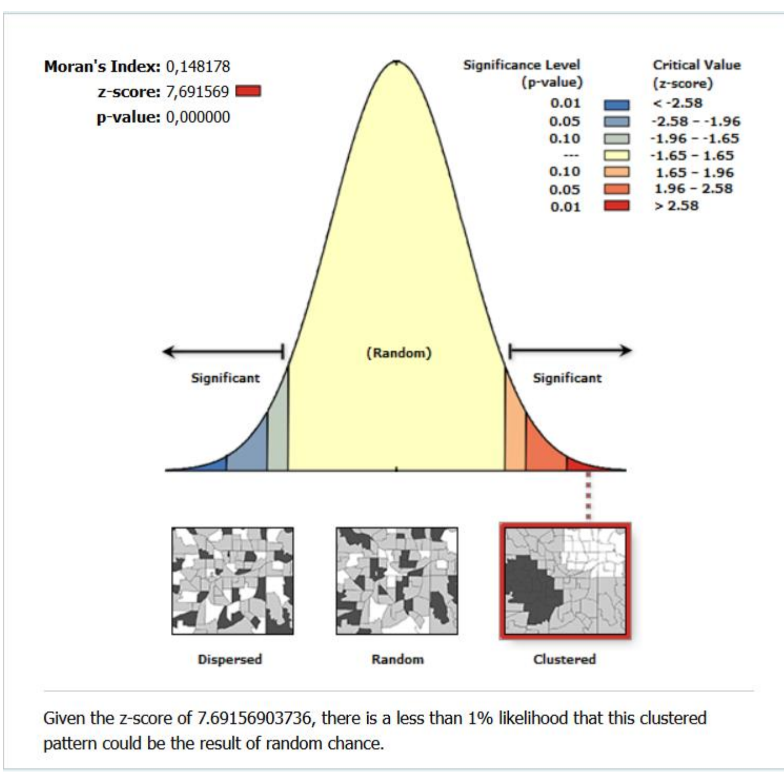
Fig. 4. Graduated Colour Map of Gross Regional Domestic Product (GRDP) per Districts in Jakarta, 2022.

Figure 4 illustrates that the first and second groups of districts, with a Gross Regional Domestic Product (GRDP) ranging from 45,673.29 to 65,372.14 billion rupiah, are predominantly located in central Jakarta and north Jakarta. These districts include Gambir (9), Cempaka Putih (2), Tanah Abang (42), Menteng (28), Senen (38), Kemayoran (19), Johar Baru (13), Tanjong Periok (43), Pademangan (29), Sawah Besar (37), Penjaringan (34), Koja (23), and Cilincing (5). The GRDP of 2,095.94 - 45,673.28 billion rupiah is distributed across the South Jakarta, West Jakarta, and East Jakarta districts, which are districts (30), (10), (26), (35), (44), (4), (11), (31), (14), (3), (1), (36), (8), (25), (6), and (7). The Jakarta Islands, specifically Kep. Seribu Selatan (21) and Kep. Seribu Utara (22), are the districts with the smallest GRDP, ranging from 1,495.93 to 2,095.93 (billion rupiah).

Moran's I Analysis and Anselin Local Moran's I

Figure 5 displays the graphic illustrating the result of spatial autocorrelation. The Moran's I value is 0.148, indicating a positive spatial correlation. The result ranges within the range of $-1 < x \leq 1$, with 1 being the maximum value for the Moran's Index. The range for Moran's I is standardized, with -1 representing the least value (showing perfect dispersion) and 1 representing the maximum value (indicating perfect clustering). Hence, the result of 0.148, although signaling a positive spatial correlation, is relatively low, implying that while there is some level of clustering, it is not notably strong. This indicates that although there is a certain level of clustering in the GRDP data, the distribution of economic activity across Jakarta's districts does not show significant spatial dependence.

Furthermore, in Fig. 5, the spatial autocorrelation demonstrates an exceptionally high *z-score* of 7.69 and a low *p*-value of less than 0.01. The *z-score* of 7.69 is significantly high (≥1.96), which is commonly used to indicate statistical significance at the 95% confidence level (Bland and Altman, 2003), suggesting that the observed spatial pattern is unlikely to be attributed to random chance. The *p*-value is less than 0.01, indicating statistical significance and consequently strengthening the validity of the results.



Moran's Index:	0,148178
Expected Index:	-0,023256
Variance:	0,000497
z-score:	7,691569
p-value:	0,000000

Fig. 5. Moran's I Spatial Autocorrelation Report Generated using ArcGIS Software.

The statistical test validation verifies that the GRDP data per Jakarta district has a positive spatial correlation and exhibits a statistically significant, non-random pattern across districts utilizing GRDP. This implies that an agglomeration has appeared among the districts in Jakarta. These results have primary importance as they prompt the assessment of alternative spatial analyses and interpolation techniques for mapping the concentration of Gross Regional Domestic Product (GRDP) between districts. Additionally, the research region displays substantial areas of low and high Gross Regional Domestic Product (GRDP) concentrations.

The Gross Regional Domestic Product (GRDP) per district within Jakarta has a dependable (reliable) clustering pattern, indicating that districts with identical GRDP values are not randomly distributed but rather physically concentrated. Hence, the authors employed Anselin Local Moran's I analysis to demonstrate districts' spatial clustering or dispersion, which generated a cluster map (Fig. 6).

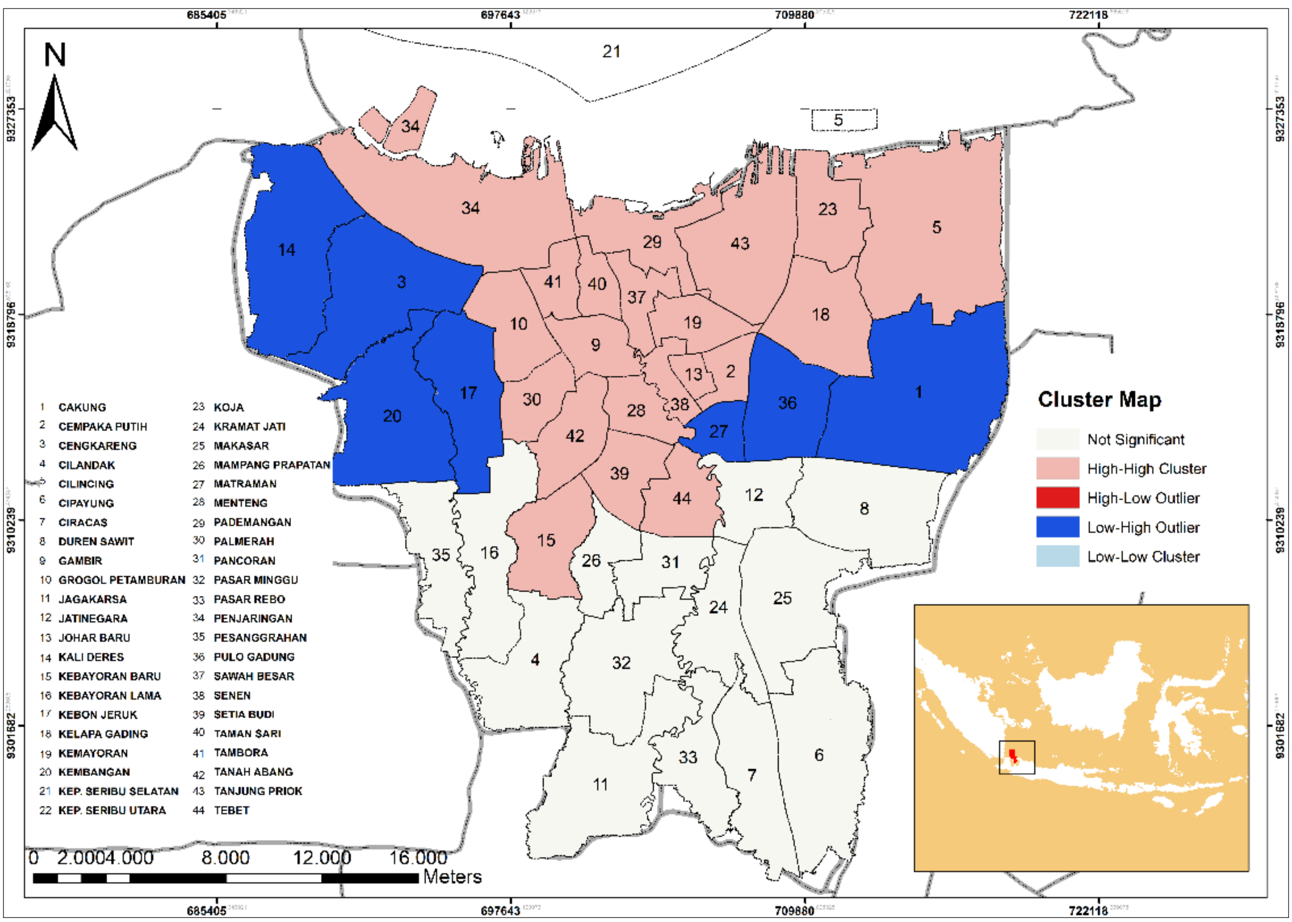


Fig. 6. Anselin Local Moran's I Cluster Map Generated using ArcGIS Software.

Figure 6 illustrates the spatial autocorrelation map showing Jakarta's cluster or agglomeration districts based on GRDP data. The statistical test defines five types of Anselin Local Morans: not-significant, high-high cluster (p-value <0.05 and Moran's index M>0), high-low cluster (p-value <0.05 and Moran's index M<0), low-high cluster (p-value <0.05 and Moran's index M<0), and low-low cluster (p-value <0.05 and Moran's index M>0).

Table 4. Clustering and Agglomeration of Districts in Jakarta, as determined by the GRDP data.

Anselin Local Moran's Criteria				
High-High Cluster (HH)	High-Low Cluster (HL)	Low-High Cluster (LH)	Low-low Cluster (LL)	Not-significant
1. Cempaka Putih (2) 2. Cilincing (5) 3. Gambir (9) 4. Grogol Petamburan (10) 5. Johar Baru (13) 6. Kebayoran Baru (15) 7. Kelapa Gading (18) 8. Kemayoran (19) 9. Koja (23) 10. Menteng (28) 11. Pademangan (29) 12. Palmerah (30) 13. Penjaringan (34) 14. Sawah Besar (37) 15. Senen (38) 16. Setia Budi (39) 17. Taman Sari (40) 18. Tambora (41) 19. Tanah Abang (42) 20. Tanjung Priok (43) 21. Tebet (44)	-	22. Cakung (1) 23.Cengkareng (3) 24. Kali Deres (14) 25. Kebon Jeruk (17) 26. Kembangan (20) 27. Matraman (27) 28. Pulo Gadung (36)	-	29. Cilandak (4) 30. Cipayung (6) 31. Ciracas (7) 32. Duren Sawit (8) 33. Jagakarsa (11) 34. Jatinegara (12) 35. Kebayoran Lama (16) 36. Kramat Jati (24) 37. Makasar (25) 38. Mampang Prapatan (26) 39. Pancoran (31) 40. Pasar Minggu (32) 41. Pasar Rebo (33) 42. Pesanggrahan (35) 43. Kep. Seribu Selatan (21) 44. Kep. Seribu Utara (22)

According to Fig. 6 and Table 4 show that there are 21 districts with high-high (HH) cluster/agglomeration of GRDP, shown by the pink color, which is primarily clustered in Central Jakarta and North Jakarta. The districts categorized as low-high (LH) clusters, shown by the color blue, are located in the western part of Jakarta (districts 3, 14, 17, and 20) and the eastern part of Jakarta (districts 1, 27, and 36). Conversely, there are 16 districts that are colored white, suggesting a lack of significance for clustering/agglomeration, and are predominantly located in the southern part of Jakarta

The existence of these economic clusters implies that central and northern Jakarta has the potential to be expanded as economic centers, drawing in more enterprises and investments that could stimulate local economies. However, if not adequately controlled, this might also make existing disparities. Spatial economic disparities have the potential to impact various aspects of urban development, such as the need for infrastructure, the flow of investments, and the distribution of social services. Therefore, policy interventions may need to prioritize the promotion of fair and equal economic growth in all districts. One such approach is to enhance the infrastructure and services in underperforming regions in order to attract private investment and enhance connectivity with more prosperous districts.

Conclusions

The paper investigated two primary inquiries: Is there any evidence of spatial clustering of Gross Regional Domestic Product (GRDP) per district? Secondly, what is the scope of these spatial clusters? The study utilized three methodologies, namely descriptive statistics centered on a graphical display, Moran's I, and Anselin Local Moran's I, which were synergistic and effectively addressed the research topics in question. The mean GRDP throughout the districts revealed a higher level of economic output in the center and northern regions of Jakarta. The Moran's I value of 0.148 indicates a positive spatial correlation, although it suggests a rather weak spatial dependency across the districts. Furthermore, the strengthened *z*-score and *p*-value ($p < 0.01$) indicate that the Gross Regional Domestic Product (GRDP) per district in Jakarta exhibits a consistent clustering pattern. This suggests that districts with similar GRDP values are not randomly spread out but rather concentrated in specific areas.

Regarding the Anselin Local Moran's I, the investigation identified multiple clusters with significant levels of activity, mainly located in the center districts of Menteng and Tanah Abang. These areas are well-known for their commercial activities. In contrast, clusters with little economic activity were discovered in the outer districts, indicating places that have the potential for economic growth. High-low and low-high outliers suggest unusual economic activities that require additional investigation for targeted governmental actions. These findings provide valuable insights for the government and economists to understand the geographical distribution of various cluster types. This knowledge can be used to develop policies that promote further concentration of economic activities in areas where significant clustering already exists or to stimulate the potential for clustering economies in other regions using district-level GRDP data. Strategies that improve current clustering and potentially foster agglomeration economies or create new agglomeration economies might be either specific to a particular cluster or informed by clusters.

Policymakers can create specific interventions in places classified as low-low clusters to promote economic activity (Wolman and Hincapie, 2015). This could involve providing tax benefits to companies (Zee et al., 2002), allocating funds for building and improving infrastructure (Gramlich, 1994), or offering assistance to developing sectors (Mason and Brown, 2013). To increase efforts in decentralising economic activities, it is advisable to promote secondary hubs in underdeveloped areas (Rasmy et al., 2021). This will help alleviate the stress on overburdened urban centers and ensure a more equitable distribution of economic gains. In addition, this study involves the utilization of spatial analysis techniques for monitoring and planning. It enables rapid reaction to change and facilitates future development by relying on empirical data.

The examination of spatial economic clusters in Jakarta conducted in this study identifies various areas that require additional inquiry to enhance comprehension of urban economic dynamics. It is acknowledged that Moran's I and Anselin Local Moran's I analysis are prone to many methodological limitations, including the modifiable areal unit problem (MAUP), assumptions of stationarity and isotropy, sensitivity to outliers, and data quality (Tiefelsdorf and Boots, 1997). These factors can significantly impact the results and analyses of spatial autocorrelation. In addition, the authors propose potential approaches for future research to tackle these concerns. These include doing sensitivity analyses and applying advanced techniques such as Geographically Weighted Regression (GWR) to overcome non-stationarity and offer more precise insights into spatial correlations at a local level.

Further research could assess the effects of particular development policies on economic clustering by employing spatial econometric models to gauge policy efficacy. Moreover, by analyzing the connections between other economic indicators, such as employment rates and industrial output, and spatial clustering, it is possible to uncover the fundamental factors that cause economic agglomeration. Conducting comparative research in other cities or regions can offer valuable insights into common and distinct economic clustering patterns, helping to refine policy interventions. Conducting such research would offer a more thorough basis for creating focused, fair, and enduring urban development strategies.

References

Abdel-Rahman, H.M., 1990. Agglomeration economies, types, and sizes of cities. J. Urban Econ. 27, 25–45. https://doi.org/https://doi.org/10.1016/0094-1190(90)90022-F

Ai, T., Wardoyo, R., 2015. Fuzzy-Klassen Model for Development Disparities Analysis based on Gross Regional Domestic Product Sector of a Region. Int. J. Comput. Appl. 123, 17–22. https://doi.org/10.5120/ijca2015905389

Alexander, M.T.F., Dziobek, M.C.H., Marini, M.M., Metreau, E., Stanger, M.M., 2017. Measure up: A better way to calculate GDP. International Monetary Fund.

Angela, A., 2021. Analysis of Gross Regional Domestic Products that Influence the Economic Growth Of Batam City 2010 – 2020. Eduvest - J. Univers. Stud. 1, 478–483. https://doi.org/10.59188/eduvest.v1i6.78

Anselin, L., 2000. Part 2 The Link between GIS and spatial analysis: GIS, spatial econometrics and social science research. J. Geogr. Syst. 2, 11–15.

Anselin, L., 1995. Local Indicators of Spatial Association—LISA. Geogr. Anal. 27, 93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x

Arauzo-Carod, J.M., Viladecans-marsal, E., 2006. Industrial location at the intra-metropolitan level: a negative binomial approach. Estud. Econ. Española 1–30.

Arbia, G., Baltagi, B.H., 2008. Spatial econometrics: Methods and applications. Springer Science \& Business Media.

Arnott, R.D., Chaves, D.B., 2012. Demographic changes, financial markets, and the economy. Financ. Anal. J. 68, 23–46. https://doi.org/10.2469/faj.v68.n1.4

Athreye, S., 2012. Agglomeration and Growth. Build. High-Tech Clust. 121–159. https://doi.org/10.1017/cbo9780511802911.007

Badan Pusat Statistik Provinsi DKI Jakarta, 2023. Jakarta Dalam Angka 2023. Jakarta.

Balchin, P.N., Bull, G.H., Kieve, J.L., 1995. Urban land economics and public policy. Bloomsbury Publishing.

Bartz, A.E., 1988. Basic Statistical Concepts Case Event Data 184.

Bland, J.M., Altman, D.G., 2003. Applying the right statistics: Analyses of measurement studies. Ultrasound Obstet. Gynecol. 22, 85–93. https://doi.org/10.1002/uog.122

Chamberlin, G., 2010. Output and expenditure in the last three UK recessions. Econ. Labour Mark. Rev. 4, 51–64. https://doi.org/10.1057/elmr.2010.113

Cheruiyot, K., 2022. Detecting spatial economic clusters using kernel density and global and local Moran’s I analysis in Ekurhuleni metropolitan municipality, South Africa. Reg. Sci. Policy Pract. 14, 307–327. https://doi.org/10.1111/rsp3.12526

Cli, A., Ord, K.J., 1973. Spatial Autocorrelation (Pion, London).

Cooke, P., 2007. Regional knowledge economies: markets, clusters and innovation. Edward Elgar Publishing.

Dabla-Norris, M.E., Ji, Y., Townsend, R., Unsal, M.F., 2015. Identifying constraints to financial inclusion and their impact on GDP and inequality: A structural framework for policy. International Monetary Fund.

Darma, D.C., 2020. Determinants of the Gross Regional Domestic Product of East Kalimantan Province: Macroeconomic Variable Review.

Dewi, N.P., Novianti, T., Hakim, D.B., 2021. Identifying spatial correlation and factors influencing regional economic growth in Southern Sumatra. J. Perspekt. Pembiayaan dan Pembang. Drh. 9, 245–256. https://doi.org/10.22437/ppd.v9i3.13422

Duranton, G., Kerr, W.R., 2018. The logic of agglomeration. New Oxford Handb. Econ. Geogr. 347–365. https://doi.org/10.1093/oxfordhb/9780198755609.013.14

Dynan, K., Sheiner, L., 2018. GDP as a measure of economic well-being.

Economides, G., Papageorgiou, D., Philippopoulos, A., 2020. Macroeconomic policy lessons for Greece.

Esposti, R., Bussoletti, S., 2008. Impact of Objective 1 funds on regional growth convergence in the European Union: A panel-data approach. Reg. Stud. 42, 159–173. https://doi.org/10.1080/00343400601142753

Figueras, A.J., Cristina, A.D., Blanco, V.J., Iturralde, I.M., 2021. The influence of agglomeration on growth: A study of argentina. Investig. Reg. 33–61. https://doi.org/10.38191/iirr-jorr.21.018

Fraumeni, B., 2022. Gross domestic product: Are other measures needed? GDP summarizes only one aspect of a country's condition; other measures in addition to GDP would be valuable. IZA World Labor 1–12. https://doi.org/10.15185/izawol.368.v2

Fujita, M., Thisse, J.-F., 1996. Economics of Agglomeration: Cities. Ind. Locat. Reg. Growth, Cambridge 378, 339–378.

Gallo, J., Ertur, C., 2005. Exploratory spatial data analysis of the distribution of regional per capita GDP in Europe, 1980-1995. Pap. Reg. Sci. 82, 175–201. https://doi.org/10.1111/j.1435-5597.2003.tb00010.x

Getis, A., 1995. Cliff, A.D. and Ord, J.K. 1973: Spatial autocorrelation. London: Pion. Prog. Hum. Geogr. 19, 245–249.

Giuliano, G., Kang, S., Yuan, Q., 2019. Agglomeration economies and evolving urban form. Ann. Reg. Sci. 63, 377–398. https://doi.org/10.1007/s00168-019-00957-4

Glaeser, E.L., 2010. Agglomeration economics. University of Chicago Press.

Gramlich, E.M., 1994. Infrastructure investment: A review essay. J. Econ. Lit. 32, 1176–1196.

Guillain, R., Gallo, J. Le, 2010. Agglomeration and Dispersion of Economic Activities in and around Paris: An Exploratory Spatial Data Analysis. Environ. Plan. B Plan. Des. 37, 961–981. https://doi.org/10.1068/b35038

Gylfason, T., Zoega, G., 2006. Natural resources and economic growth: The role of investment. World Econ. 29, 1091–1115. https://doi.org/10.1111/j.1467-9701.2006.00807.x

Halmos, K., 2011. The effect of FDI, exports and GDP on income inequality in 15 Eastern European countries. Acta Polytech. Hungarica 8, 123–136.

Hasan, M.M., Hossain, B.M.S., Sayem, M.A., 2022. Determining the Impact of Economic Factors to the Gross Domestic Product in Bangladesh. Int. J. Econ. Financ. Issues 12, 37–40. https://doi.org/10.32479/ijefi.12686

Hong, G., Macao, K., Bay, G., Gba, A., 2021. Delineation of Urban Agglomeration Boundary Based on Multisource Big Data Fusion — A Case Study of. Remote Sens.

Ibe, O.C., 2014. Introduction to Descriptive Statistics. Fundam. Appl. Probab. Random Process. 253–274. https://doi.org/10.1016/b978-0-12-800852-2.00008-0

Jakarta Government, 2020. One Maps Jakarta Satu [WWW Document]. URL https://website-jakarta-satu-jakartagis.hub.arcgis.com/pages/download (accessed 11.22.23).

Jurun, E., Pivac, S., 2011. Comparative regional GDP analysis: case study of Croatia. Cent. Eur. J. Oper. Res. 19, 319–335.

Kalimeris, P., Bithas, K., Richardson, C., Nijkamp, P., 2020. Hidden linkages between resources and economy: A "Beyond-GDP" approach using alternative welfare indicators. Ecol. Econ. 169. https://doi.org/10.1016/j.ecolecon.2019.106508

Kim, J., others, 2016. The effects of demographic change on GDP growth in OECD economies.

Kondo, K., 2021. Testing for Global Spatial Autocorrelation in Stata: Moransi version 1.21. Stat. Softw. Components S458473, Bost. Coll. Dep. Econ. 2021, 1–10.

Kosareva, N., Polidi, T., 2017. Assessment of gross urban product in Russian cities and its contribution to Russian GDP in 2000-2015. Russ. J. Econ. 3, 263–279. https://doi.org/10.1016/j.ruje.2017.09.003

Kurpayanidi, K., Abdullaev, A., Mukhsinova, S., 2021. Жамият ва инновациялар – Общество и инновации – Society and innovations Analysis of the macroeconomic policy of the Republic of Uzbekistan O ‘ zbekiston Respublikasining makroiqtisodiy siyosatini tahlil qilish Анализ макроэкономической политики Республики 3–7.

Larson, M.G., 2006. Descriptive statistics and graphical displays. Circulation 114, 76–81. https://doi.org/10.1161/CIRCULATIONAHA.105.584474

Li, H., Calder, C.A., Cressie, N., 2007. Beyond Moran's I: Testing for spatial dependence based on the spatial autoregressive model. Geogr. Anal. 39, 357–375. https://doi.org/10.1111/j.1538-4632.2007.00708.x

Lu, Y., Cao, K., 2019. Spatial analysis of big data industrial agglomeration and development in China. Sustain. 11, 1–22. https://doi.org/10.3390/su11061783

Lyu, C., Wang, K., Zhang, F., Zhang, X., 2018. GDP management to meet or beat growth targets. J. Account. Econ. 66, 318–338.

Mason, C., Brown, R., 2013. Creating good public policy to support high-growth firms. Small Bus. Econ. 40, 211–225.

McCann, P., Van Oort, F., 2019. Theories of agglomeration and regional economic growth: a historical review. Handb. Reg. growth Dev. Theor. 6–23.

Mishra, P., Pandey, C.M., Singh, U., Gupta, A., 2018. Scales of measurement and presentation of statistical data. Ann. Card. Anaesth. 21, 419–422. https://doi.org/10.4103/aca.ACA_131_18

Mohanty, A., 2019. Measuring GDP and Economic Growth: An Economic Barometer. Int. J. Tax Econ. Manag. 2, 42–58. https://doi.org/10.35935/tax/21.5842

Odland, J., 2020. Spatial autocorrelation.

OECD, 2008. OECD Regions at a Glance 2007. https://doi.org/https://doi.org/https://doi.org/10.1787/reg_glance-2007-en

Ong Tze San, 2013. Factors Affecting the Price of Housing in Malaysia. Financ. Bank. An Online Int. Mon. J. 415.

Özyılmaz, A., 2022. Relationship Between Inflation and Economic Growth in EU Countries. J. Econ. Policy Res. / İktisat Polit. Araştırmaları Derg. 9, 425–438. https://doi.org/10.26650/jepr1132170

Paun, C.V., Musetescu, R.C., Topan, V.M., Danuletiu, D.C., 2019. The impact of financial sector development and sophistication on sustainable economic growth. Sustain. 11, 1–21. https://doi.org/10.3390/su11061713

Putra, A.S., Tong, G., Pribadi, D.O., 2020. Spatial analysis of socio-economic driving factors of food expenditure variation between provinces in Indonesia. Sustain. 12, 1–18. https://doi.org/10.3390/su12041638

Putri Yunita, M., Dewitasari, Y., Riadi, S., 2021. Analysis of Leading Economic Sector in South Jakarta Administrative City. Maj. Ilm. Bijak 18, 19–30. https://doi.org/10.31334/bijak.v19i1.1958

Rasmy, M., Latif, T.A., Ibrahim, A.A.M., 2021. The Sustainable Strategy to Create Decentralized Economic Hubs for Regional Development BT - Advanced Studies in Efficient Environmental Design and City Planning, in: Trapani, F., Mohareb, N., Rosso, F., Kolokotsa, D., Maruthaveeran, S., Ghoneem, M. (Eds.), . Springer International Publishing, Cham, pp. 225–243.

Rey, S., Arribas-Bel, D., Wolf, L.J., 2023. Local Spatial Autocorrelation. Geogr. Data Sci. with Python 157–184. https://doi.org/10.1201/9780429292507-9

Roemer, M., Gugerty, M.K., 1997. DISCUSSION PAPERS Does Economic Growth Reduce Poverty?

Rusiawan, W., Tjiptoherijanto, P., Suganda, E., Darmajanti, L., 2015. System Dynamics Modeling for Urban Economic Growth and CO2 Emission: A Case Study of Jakarta, Indonesia. Procedia Environ. Sci. 28, 330–340. https://doi.org/10.1016/j.proenv.2015.07.042

Saudi, S.N.D., Anshar, M.A., Kausar, A., Muchsidin, M., Muchsidin, F.F., 2021. Analysis of Economic Growth and Income Disparity on Inter-Regional Welfare. Point View Res. Econ. Dev. 2, 68–87.

Sbergami, F., 2002. Agglomeration and Economic Growth: Some Puzzles. HEI Work. Pap. 1–34.

Song, Y., Lee, K., Anderson, W.P., Lakshmanan, T.R., 2012. Industrial agglomeration and transport accessibility in metropolitan Seoul. J. Geogr. Syst. 14, 299–318. https://doi.org/10.1007/s10109-011-0150-z

Stahel, A.W., 2021. Real-World Economics Review. Real-World Econ. Rev. 217–238.

Suhartono, D.T., 2020. Gross Domestic Regional Product Reconciliation and Compilation Application Development in Sulawesi Selatan. J. Mantik 4, 2005–2012.

Sutrasna, Y., Duha, J., 2023. The Effect of the Number of Population and Gross Domestic Regional Product (GDRP) on Regional Original Revenue (PAD) in The Regency/City of West Java Province, Indonesia. Tec Empres. 18, 176–185.

Taylor, J.B., 2000. The policy rule mix: a macroeconomic policy evaluation. Robert Mundell Festschrift 43, 28.

Thisse, J.-F., 2019. Economics of Agglomeration, Oxford Research Encyclopedia of Economics and Finance. https://doi.org/10.1093/acrefore/9780190625979.013.152

Tiefelsdorf, M., Boots, B., 1997. A note on the extremities of local Moran's Iis and their impact on global Moran's I. Geogr. Anal. 29, 248–257. https://doi.org/10.1111/j.1538-4632.1997.tb00960.x

Tiefelsdorf, M., Boots, B., 1995. The Exact Distribution of Moran's I. Environ. Plan. A Econ. Sp. 27, 985–999. https://doi.org/10.1068/a270985

Turok, I., McGranahan, G., 2013. Urbanization and economic growth: The arguments and evidence for Africa and Asia. Environ. Urban. 25, 465–482. https://doi.org/10.1177/0956247813490908

Wang, H., Lu, X., Guo, Q., Zhang, Y., 2023. The Spatiotemporal Measurement of Coordinated Development of Resource-Environment-Economy Based on Empirical Analysis from China's 30 Provinces. Sustain. 15. https://doi.org/10.3390/su15086995

Wolman, H. (Hal), Hincapie, D., 2015. Clusters and Cluster-Based Development Policy. Econ. Dev. Q. 29, 135–149. https://doi.org/10.1177/0891242413517136

Yang, Z., Sliuzas, R., Cai, J., Ottens, H.F.L., 2012. Exploring spatial evolution of economic clusters: A case study of Beijing. Int. J. Appl. Earth Obs. Geoinf. 19, 252–265. https://doi.org/https://doi.org/10.1016/j.jag.2012.05.017

Yellapu, V., 2018. Full Text Introduction. Descr. Stat. 4, 60–63. https://doi.org/10.4103/IJAM.IJAM

Zee, H.H., Stotsky, J.G., Ley, E., 2002. Tax Incentives for Business Investment: A Primer for Policy Makers in Developing Countries. World Dev. 30, 1497–1516. https://doi.org/https://doi.org/10.1016/S0305-750X(02)00050-5

Zhao, Y., Zhang, G., Zhao, H., 2021. Spatial Network Structures of Urban Agglomeration Based on the Improved Gravity Model: A Case Study in China's Two Urban Agglomerations. Complexity 2021, 6651444. https://doi.org/10.1155/2021/6651444

Zhu, X., Wang, Q., Zhang, P., Yu, Y., Xie, L., 2021. Optimizing the spatial structure of urban agglomeration: based on social network analysis. Qual. Quant. 55, 683–705. https://doi.org/10.1007/s11135-020-01016-3

النمذجة الجغرافية لتكتلات/ تجمعات البيانات الاقتصادية للناتج المحلي الإجمالي الإقليمي باستخدام تحليل مؤشر موران: دراسة حالة جاكرتا، إندونيسيا

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المستخلص. الناتج المحلي الإجمالي الإقليمي هو مؤشر إحصائي يُستخدم لقياس الحجم الاقتصادي لمنطقة معينة. تُعد الاقتصادات الحضرية عاملًا حيويًا في دفع عجلة النمو الوطني، لا سيما في الدول النامية التي تشهد تطورًا سريعًا في التحضر. تمثل جاكرتا، إندونيسيا، مثالًا على اقتصاد حضري يتمتع بتأثير كبير على الأنماط الاقتصادية الوطنية. تهدف هذه الدراسة إلى تعزيز فهم الأنماط المكانية للنشاط الاقتصادي في جاكرتا باستخدام نظم المعلومات الجغرافية وتحليل مؤشر موران لبيانات الناتج المحلي الإجمالي الإقليمي. غالبًا ما أغفلت الدراسات السابقة الأبعاد المكانية للتكتلات الاقتصادية، والتي تُعد ضرورية للتخطيط الحضري وصياغة السياسات بشكل شامل. تسعى هذه الدراسة إلى معالجة الفجوة في الفهم المرتبطة بتكوين وتأثير التكتلات الاقتصادية على النمو الاقتصادي الحضري من خلال دراسة حالة جاكرتا بشكل دقيق. تعتمد الدراسة على تقنيات الارتباط الذاتي المكاني للكشف عن أنماط التكتلات الاقتصادية وفحصها. علاوة على ذلك، يناقش الباحثون بيانات الناتج المحلي الإجمالي الإقليمي لعام ٢٠٢٢، التي تم الحصول عليها من وكالة الإحصاء في جاكرتا، والتي تقدم رؤية شاملة عن الأداء الاقتصادي في مختلف المناطق. أظهرت نتائج تحليل الارتباط الذاتي المكاني ومؤشر موران تركيزات ملحوظة للنشاط الاقتصادي في وسط وشمال جاكرتا، مما يشير إلى مناطق ذات إنتاج اقتصادي كبير وآفاق توسع مستقبلية. تتميز هذه التكتلات بتركيز الأنشطة التجارية والصناعية، مما يبرز فرصًا للتدخلات السياسية لتعزيز التنمية الاقتصادية. تؤكد الدراسة على أهمية هذا التحليل لمخططي المدن وصناع السياسات، حيث توفر رؤى تفصيلية حول المشهد الاقتصادي لمناطق المدينة، مما يساهم في توجيه التخطيط الاقتصادي الشامل والمستدام.

الكلمات المفتاحية: الناتج المحلي الإجمالي الإقليمي، التكتلات الاقتصادية، نظم المعلومات الجغرافية، تحليل مؤشر موران، الارتباط الذاتي المكاني، جاكرتا.