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Spatial Autocorrelation of East Java's Economic Growth Using Cluster-Based Weights

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Abstract

This study incorporates a spatial clustering technique into the formation of a spatial weight matrix as an alternative to the traditional exogenous matrix, aiming to better capture spatial dependencies. The approach is applied to analyze the spatial autocorrelation of economic growth in East Java's regencies and municipalities using 2019–2021 data. Spatial clusters are identified based on GDP growth (GGDP), Human Development Index (HDI), population density (Dens), and geographical coordinates. These clusters are used to define a customized spatial weight matrix, where regions within the same cluster are designated as neighbors. Moran's I, calculated using the customized spatial weight matrix, detects significant spatial autocorrelation in GDP growth for all three years, with consistently lower p-values compared to the traditional contiguity-based matrix. For example, in 2020, Moran's I using the customized matrix yielded a p-value of 0.099 (significant at the 10% level), while the traditional matrix produced a non-significant p-value of 0.7965. These results demonstrate that spatial clustering extends the scope of spatial interaction beyond adjacent regions to include those with similar characteristics. The findings highlight the effectiveness of this method in providing a more nuanced and robust framework for analyzing spatial dependencies in economic growth.

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INTRODUCTION

In spatial data modeling, a spatial weight matrix plays a crucial role in quantifying spatial relationships among features in a dataset (Anselin 1988, Arbia 2014, Beenstock and Felsenstein 2019). Traditionally, these matrices are defined exogenously, based on concepts such as contiguity or distance, which do not consider the observed features or variables. While straightforward, such approaches often fail to capture the true nature of spatial dependence, potentially leading to errors in spatial autocorrelation tests, such as Moran's I or Geary's C (Getis and Aldstadt 2004). To address this limitation, several studies (Getis and Aldstadt 2004, Aldstadt and Getis 2006) propose the endogenous formation of spatial weight matrices, leveraging observed data to better reflect spatial interactions. Although promising, this approach requires complex calculations and careful implementation.

East Java, Indonesia, provides an ideal context for studying spatial interactions, particularly in the realm of economic growth. As one of Indonesia's most economically dynamic provinces, East Java comprises 38 regencies and municipalities with diverse socio-economic characteristics and varying levels of development. Understanding spatial dependencies in GDP growth is critical for designing effective regional development policies, such as establishing economic zones that strategically leverage interdependencies among regencies. Designating such zones—each with a central hub or growth center—can promote balanced development by ensuring that resources and opportunities are distributed strategically across regions. Regional interdependence, a key driver of growth, can be analyzed using spatial autocorrelation methods, such as Exploratory Spatial Data Analysis (ESDA) and Spatial Econometric Modeling (Tian et al. 2010, Ma et al. 2016). However, the accuracy of these analyses depends significantly on the spatial weight matrix used.

Spatial clustering offers a novel approach to improving the formation of spatial weight matrices. By grouping regions with similar characteristics—including economic indicators such as GDP growth, Human Development Index (HDI), and population density—spatial clustering integrates endogenous concepts into spatial weight matrix construction. Clustering techniques, such as K-Means, hierarchical clustering, and density-based methods (Kaufman and Rousseeuw 2009, Landau et al. 2011), are commonly used to group locations based on similarity. When applied with a contiguity constraint, these techniques, such as zonation and regionalization (Murray and Grubesic 2002, Duque et al. 2007), become spatial clustering methods that ensure geographically contiguous clusters.

A widely used and efficient algorithm for spatial clustering is SKATER (Spatial 'K'luster Analysis by Tree Edge Removal) (Assunção et al. 2006). SKATER creates spatially contiguous clusters by constructing a Minimum Spanning Tree (MST) from a connectivity graph, where nodes represent regions, edges represent spatial relationships, and edge costs reflect dissimilarity between regions. The MST is trimmed to form clusters that respect geographic contiguity, making SKATER particularly suitable for analyzing regional economic dynamics.

This study integrates spatial clustering into the development of a spatial weight matrix and applies it to analyze the spatial autocorrelation of economic growth across East Java's regencies and municipalities using data from 2019 to 2021. By employing Moran's I to evaluate the significance of spatial autocorrelation, the study compares the performance of the proposed spatial weight matrix against a traditional contiguity-based matrix. The results provide valuable insights into the spatial dynamics of East Java's economic growth, offering a robust framework for effective regional development planning.

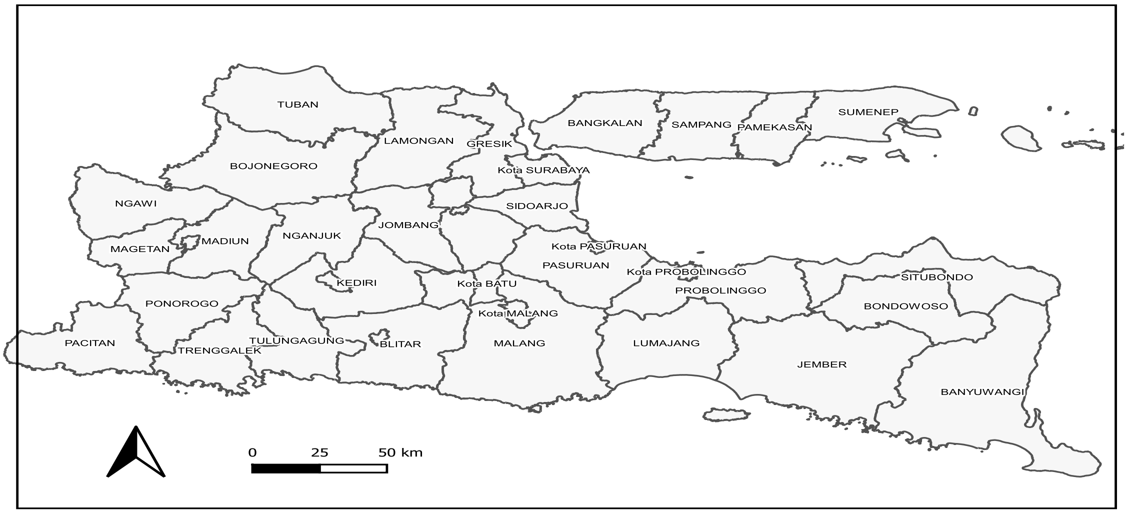


Figure 1. Map of East Java's Regencies/Municipalities

RESEARCH METHODS

To answer the objectives, this study conducts spatial econometric analysis, with a particular focus on examining the spatial autocorrelation of regional economic growth across East Java's regencies and municipalities. The analysis involves developing a novel approach for constructing a spatial weight matrix and evaluating its performance by comparing it to a traditional contiguity-based matrix.

East Java, one of Indonesia's provinces, consisting of 38 regencies and municipalities, is the area under study. The map of the administrative boundaries of East Java is presented in Figure 1. Three socio-economic variables are observed each regency: Gross Domestic Product growth ($GGDP$), Human Development Index (HDI), and Population Density ($Dens$). Data for these variables are based on observations for the years 2019, 2020, and 2021, provided by the Indonesian Statistics Bureau. Details and notation of these variables are presented in Table 1.

The selection of these variables for this study is motivated by their theoretical and empirical relevance to regional economic growth and their potential role in influencing spatial interactions.

GDP Growth ($GGDP$) serves as the primary indicator of regional economic performance, reflecting the rate at which a region's economy is expanding. It is a direct measure of economic growth and a critical factor in understanding regional disparities and spatial dependencies. Spatial clustering of $GGDP$ can reveal how economic growth in one region influences or is influenced by its neighbors, aligning with theories of spatial spillovers in regional development (Tian *et al.* 2010, Ma *et al.* 2016).

Human Development Index (HDI) is a composite measure of health, education, and income that captures the overall quality of life in a region. Ranis et al. (2000) highlight the mutual relationship between human development and economic growth, where higher HDI levels can drive sustainable economic expansion. Spatially, regions with similar HDI values often exhibit interconnected development trajectories, underscoring its relevance to spatial interactions in economic growth.

Population density ($Dens$) reflects the spatial concentration of people within a region and is a proxy for market potential and resource availability. Yegorov (2009) demonstrates that population density plays a role in shaping economic outcomes, with the benefits of density depending on initial economic conditions and spatial configurations. Regions with similar population densities often share comparable development challenges and opportunities, making $Dens$ a critical variable for spatial clustering.

By incorporating these variables into the spatial clustering process, this study captures both the socio-economic and geographical dimensions of regional interactions. These variables not only influence economic outcomes individually but also interact to shape the spatial patterns of economic growth. This approach ensures that the spatial clusters are informed by factors relevant to economic dynamics, enhancing the explanatory power of the customized spatial weight matrix.

Table 1. The Economic-Growth Related Variables

Variable	Source
$GGDP_{it}$: Economic Growth of regency/municipality i at year t HDI_{it}: Human development Index of regency/ municipality i at year t $Dens_{it}$: Density of regency/ municipality i at year t	Statistics Indonesia
$i = 1, \ldots, 38, t = 2019, 2020, 2021$	

Source: Data Processed, 2024

To construct the proposed spatial weight matrix, this study employs the SKATER algorithm, as outlined by Assunção *et al.* (2006), to generate contiguity-constrained clusters for the 38 regencies and municipalities of East Java. These clusters are formed based on geographic location and three socio-economic variables (GDP growth, Human Development Index, and population density). The algorithm is applied separately for each year's dataset—2019, 2020, and 2021—to account for potential temporal variations in the data.

Unlike the traditional contiguity-based approach, where the elements of $n \times n$ spatial weight matrix W are defined as:

$$w_{ij} = \begin{cases} 1, & \text{if region } i \text{ and } j \text{ share borders} \\ 0, & \text{otherwise} \end{cases} \quad \text{........ (1)}$$

The SKATER algorithm forms clusters based on attribute similarity and geographic contiguity. These clusters are then used to define the modified spatial weight matrix. In this matrix, regions within the same cluster are considered neighbors, and their corresponding weights are set to 1, while regions in different clusters are assigned a weight of 0. Mathematically, the elements of the modified spatial weight matrix are:

$$w_{ij} = \begin{cases} 1, \text{ if regions } i \text{ \& } j \text{ are in the same cluster} \\ 0, \quad \text{otherwise} \end{cases} \quad \ldots (2)$$

here $i, j = 1, \ldots, 38$. This clustering approach ensures that every regency or municipality has at least one neighboring region. The resulting spatial weight matrix incorporates both attribute similarity and geographic proximity, providing a customized framework for analyzing spatial autocorrelation.

To clearly define how SKATER works in this study, the following notations are used:

- $\boldsymbol{x}_i = (GGDP_i, HDI_i, Dens_i)$ is an attribute vector for regency/municipality $i, i = 1, \ldots, 38$ as the spatial unit
- $G = (V, L)$ is a connectivity graph, with a set of nodes V and a set of edges L
- $(v_1, \ldots, v_{38})$ is a sequence of nodes (as members of V) each represents regency/municipality $i, i = 1, \ldots, 38$
- (v_i, v_j) is an edge connecting regencies/municipalities v_i and regency/municipality v_j when those two regencies/municipalities are adjacent.
- $d(i, j)$ is a cost associated with an edge (v_i, v_j) by measuring the dissimilarity between regencies/municipalities i and j using their attribute vectors $(\boldsymbol{x}_i, \boldsymbol{x}_j)$.

Whereas, the steps of SKATER algorithm are:

1. Measure cost/dissimilarity between adjacent regencies/municipalities i and j using their attribute vectors $(\boldsymbol{x}_i, \boldsymbol{x}_j)$:

$$d(i, j) = d(\boldsymbol{x}_i, \boldsymbol{x}_j) = (GGDP_i - GGDP_j)^2 (HDI_i - HDI_j)^2 + (Dens_i - Dens_j)^2 \quad \text{.................................. (3)}$$

2. Associate the cost in step 1 with an edge (v_i, v_j)

3. Find an MST from the connectivity graph $G = (V, L)$ using Prim's Algorithm:
   i. Choose any node v_i in the complete set of nodes V, setting the first tree
   $$T_k = T_1 = (\{v_i\}, \phi)$$
   ii. Find the edge of lowest cost d_{ij} (namely l' in L) which connects any node v_i in T_k to another node v_j, belonging to V but not to T_k
   iii. Add v_j and l' to the tree T_k, and form a new tree T_{k+1}

   Repeat step ii until all nodes have been included in the tree T_n
4. Breaking up the MST from step 3 into a set of k contiguous clusters. The partition algorithm uses intra-cluster square deviation, which is defined as:

$$SSD_k = \sum_{i=1}^{n_k}\left(GGDP_i - \overline{GGDP^k}\right)^2 + \sum_{i=1}^{n_k}\left(HDI_i - \overline{HDI^k}\right)^2 + \sum_{i=1}^{n_k}\left(Dens_i - \overline{Dens^k}\right)^2 \quad (4)$$

Where n_k is the number of regencies/ municipalities in tree k, and the average of each variable. ($\overline{GGDP^k}, \overline{HDI^k}, \overline{Dens^k}$) is taken over the regencies/municipalities in tree k. The definition in equation (2) is then used to calculate an objective function:

$$f\left(S_l^T\right) = SST_T - (SST_{Ta} - SST_{Tb}) \quad (5)$$

Where, having a configuration S_l^T, obtained by cutting out the edge l from the tree T, such that it is divided into Ta and Tb. The algorithm works as follows:

   i. Start the graph $G^* = (T_0)$, in which T_0 is the MST from step 3
   ii. Identify the edge l in T_0 with the highest $f\left(S_l^{T_0}\right)$
   iii. While the number of trees in $G^* < k$ (the defined number of clusters), repeat step iv, v and vi.
   iv. For each tree T_i in G^* identify edge l in T_i with the highest $f\left(S_l^{T_i}\right)$
   v. Choose the T_i among all T_i in G^* with the highest $f\left(S_l^{T_i}\right)$
   vi. Divide T_i into two new subtrees and update G^*

Spatial autocorrelation in this study is analyzed using Moran's I, a widely used statistics introduced by Moran (1950) to measure the degree of which a variable is spatially clustered, dispersed or randomly distributed. Moran's I quantifies spatial relationships by evaluating how similar or dissimilar values of a variable across geographic locations. For a variable X_i, where $i = 1, \dots, n$ represents the index for each location, Moran's I is defined as:

$$I = \frac{\sum_{j=1}^{n}\sum_{i=1}^{n} w_{ij}(X_i - \bar{X})(X_j - \bar{X})}{\sum_{i=1}^{S}(X_i - \bar{X})^2} \quad (6)$$

Here, w_{ij} is the ij-th element spatial weight matrix W, for $i, j = 1, 2, \dots, n$. This matrix capture the spatial relationships between regions, allowing Moran's I to account for both attribute similarity and geographic proximity. The index ranges from -1 to 1. A positive value indicates that nearby locations have similar observed values of X, suggesting clustering, while a negative value indicates that nearby locations have dissimilar observed values, suggesting dispersion. Values near zero suggest a random spatial distribution. This range provides a clear interpretation of the degree and nature of spatial autocorrelation.

Under the null hypotheses of spatial randomness, using $n = 38$, the index has expected value:

$$E(I) = \frac{-1}{n-1} \quad (7)$$

and variance:

$$var(I) = \frac{nS_4 - S_3S_1(1-2n)}{(n-1)(n-2)(n-3)\left(\sum_{j=1}^{n}\sum_{i=1}^{n} w_{ij}\right)^3} \quad (8)$$

in which:

$$S_1 = \sum_{j=1}^{n}\sum_{i=1}^{n}\left(w_{ij} + w_{ji}\right)^2,\ S_2 = \sum_{i=1}^{n}\left(\sum_{j=1}^{n} w_{ij} + \sum_{j=1}^{n} w_{ji}\right)^2$$

$$S_3 = \frac{n^{-1}\sum_{i=1}^{n}(X_i - \bar{X})^4}{\left(n^{-1}\sum_{i=1}^{n}(X_i - \bar{X})^2\right)^2},\ S_4 = (n^2 - 3n + 3)S_1 - nS_2 + 3\left(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\right)^2 \quad (9)$$

An inference for Moran's I can be made by employing approximately standard normal distribution:

$$Z = \frac{I - E(I)}{\sqrt{var(I)}} \sim N(0,1) \quad (10)$$

Where, an extreme value of this statistic leads to a rejection of the null hypothesis.

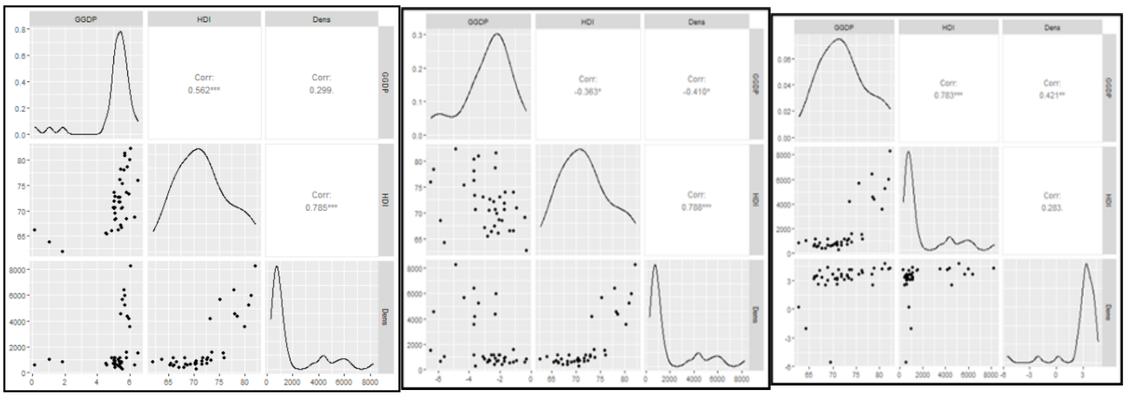
To evaluate the effectiveness of the proposed spatial weight matrix, a comparative analysis is conducted using Moran's test. The test is performed twice: first using the traditional contiguity-based spatial weight matrix, with elements defined as in equation (1), and then using the customized spatial weight matrix, with elements defined as in equation (2). The comparative analysis focuses on the significance levels (p-values) of the Moran's I results from both tests. A lower p-value indicates stronger statistical evidence of spatial autocorrelation, suggesting that the corresponding spatial weight matrix is more representative of the actual spatial relationships. This approach allows for an objective evaluation of whether the customized spatial weight matrix better captures the spatial patterns in the data compared to the traditional method.

RESULTS AND DISCUSSION

The results of this study demonstrate how integrating the concept of spatial clustering into the formation of a spatial weight matrix, based on variables relevant to the variable under study, enhance the ability to capture spatial interactions between regions, as reflected in the magnitude and significance of spatial autocorrelation for economic growth across East Java's regencies/municipalities during the 2019–2021 period.

The exploratory analysis was conducted separately for each year (2019, 2020, and 2021) to understand the relationship between GGDP, HDI, and Dens. Pearson's correlation coefficients were used to assess the linear relationships between the variables, as shown in figure 2 (a), (b), and (c). Each figure includes scatter plots and the corresponding correlation coefficients for GGDP with HDI and GGDP with Dens. The analysis indicates that HDI and Dens have varying degrees of correlation with GGDP across the years. For instance:

In 2019 (Figure 2a), a moderate positive correlation ($r = 0.562$) is observed between GGDP and HDI, while the relationship between GGDP and Dens shows a weaker correlation ($r = 0.299$). In 2020 (Figure 2b), the correlation between GGDP and HDI becomes slightly negative ($r = -0.363$), suggesting potential changes in the dynamics of regional development during this period. Similarly, the correlation between GGDP and Dens is negative ($r = -0.410$), indicating a possible shift in the relationship between economic growth and population density. In 2021(Figure 2c), the relationship between GGDP and HDI becomes strongly positive ($r = 0.768$), and the correlation between GGDP and Dens strengthens ($r = 0.421$).



(a) (b) (c)

Figure 2. Pearson's Correlation between GGDP,HDI and Dens of the 38 East Java's Regencies/Municipalities, for (a) 2019, (b) 2020, (c) 2021
Source: Data Processed, 2024

The scatter plots reveal that while HDI and Dens are related to GGDP, the relationships are not strictly linear. This is particularly evident in the variation and dispersion of data points in each scatter plot, suggesting that additional factors or nonlinear interactions may influence the relationship between these variables. These findings underscore the complexity of regional economic growth and highlight the need for advanced spatial analysis techniques, such as the use of a customized spatial weight matrix, to capture these nuanced interactions.

The spatial distribution of GDP growth across East Java's regencies and municipalities for the years 2019, 2020, and 2021 is presented in Figure 3, Figure 4, and Figure 5, respectively. In those maps darker shades indicate higher GDP growth, while lighter shades represent lower growth.

Figure 3 shows that in 2019, regions such as Surabaya and surrounding areas exhibit relatively higher GDP growth, forming a distinct cluster of economic activity in the north-central part of East Java. Conversely, lower GDP growth is observed in more peripheral regions, such as the southern and eastern municipalities. Figure 4 highlights the impact of economic disruptions in 2020, with a general decline in GDP growth across many regions. The previously identified growth cluster in Surabaya shows reduced intensity, while other areas, such as the southern regencies, exhibit further stagnation. Figure 5 depicts a partial recovery in 2021, with new clusters of moderate growth emerging in the eastern regions, suggesting shifting dynamics in regional economic interactions.

The observed clustering patterns suggest the presence of spatial autocorrelation, where regions with similar economic growth rates tend to be geographically proximate. This supports the initial assumption of spatial interaction in East Java's regional GDP growth. To formally test the significance of these spatial interactions, this study employs the SKATER algorithm. SKATER identifies clusters of regions that are both geographically proximate and similar in terms of economic growth and its associated factors, such as HDI and population density. These clusters are then used to define the neighborhood structure for each region, forming the basis of the spatial weight matrix.

The spatial weight matrix derived from SKATER allows for a tailored representation of spatial relationships, capturing both proximity and attribute similarity. This matrix is subsequently used to calculate Moran's I index and conduct Moran's test, providing a quantitative measure of the strength and significance of spatial autocorrelation. The alignment of observed patterns in the distribution maps with the results of Moran's test will validate the appropriateness of the customized spatial weight matrix in capturing spatial interactions.

The application of the SKATER algorithm to define neighbors and clusters for the formation of the spatial weight matrix in this study presented several challenges. An improper choice of k, the number of clusters, can result in clusters with only one region, leading to isolated regions without neighbors. According to the rule in (2) this would produce a spatial weight matrix with a row of all zeros, violating the fundamental requirement for spatial weight matrices, which ensures that every region has at least one neighbor. To address this issue, various values of kkk were tested using East Java's growth-related data. For all years analyzed, $k = 3$ was found to be the smallest value that consistently produced clusters where every region had at least one neighbor. Thus, setting $k = 3$ ensures a valid spatial weight matrix, meeting the required properties for spatial autocorrelation analysis.

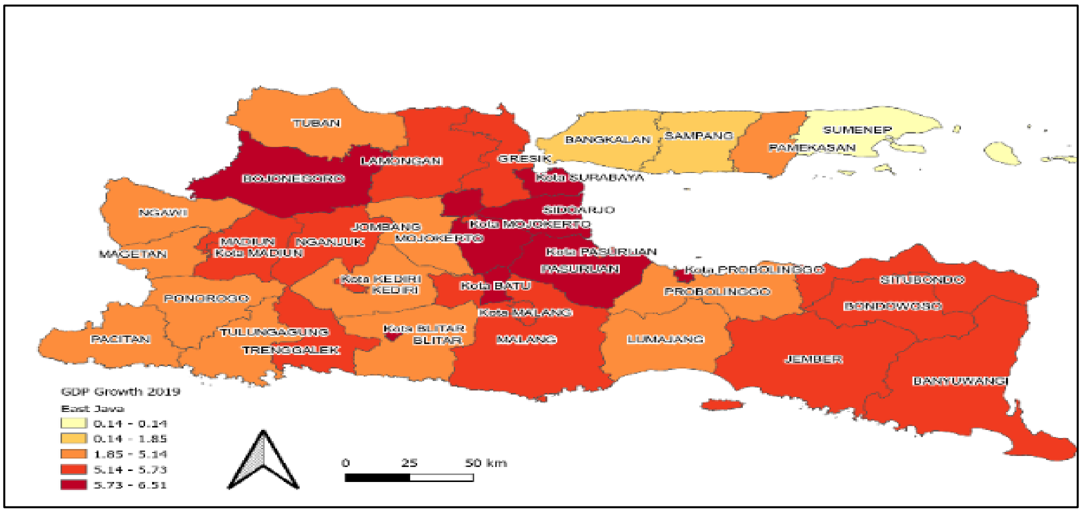


Figure 1. Spatial Distribution Map of East Java's regional GDP Growth 2019
Source: Data Processed, 2024

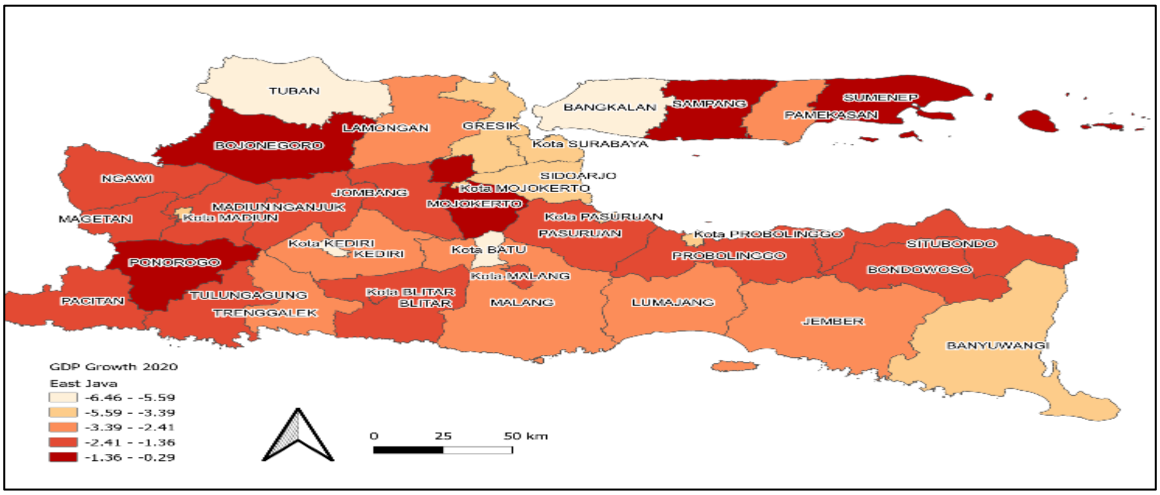


Figure 4. Spatial Distribution Map of East Java's regional GDP Growth 2020
Source: Data Processed, 2024

The initial plan was to form spatial clusters based on GGDP, HDI, Dens, and the geographical locations of each regency/municipality. However, for $k = 3$, this approach successfully produced spatially contiguous clusters with more than one member only for the 2019 data. For the 2020 data, spatially contiguous clusters were obtained using GGDP and HDI, while for the 2021 data, the clusters were formed using HDI and Dens.

The spatially contiguous clusters of East Java's regencies/municipalities based on 2019 GDP growth, HDI, and population density are visualized in figure 6. Each cluster represents regions with similar economic and socio-economic characteristics, reflecting spatial dependencies. These clusters were used to define the elements of the customized spatial weight matrix, following the definition in (2).

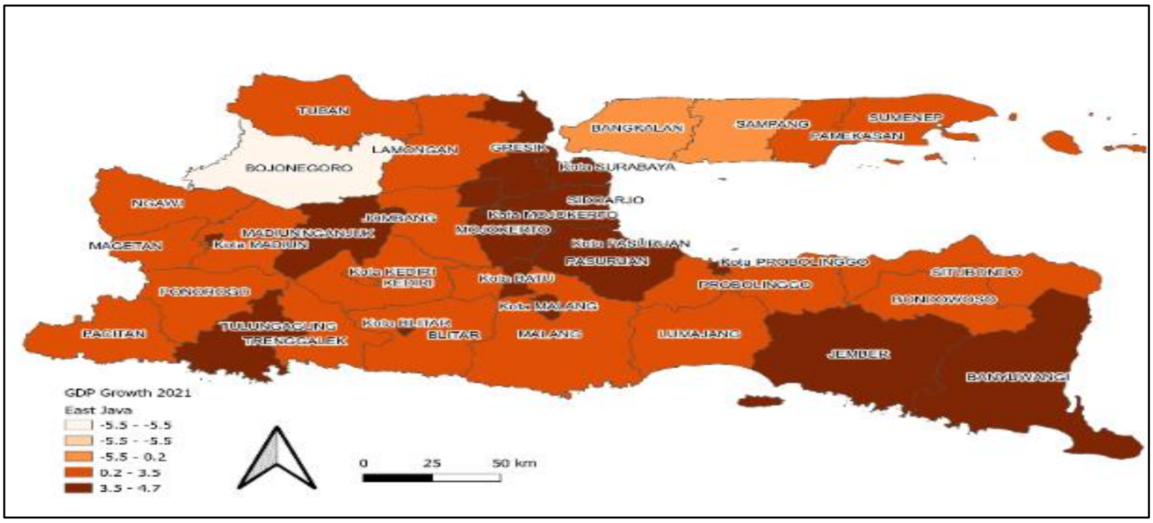


Figure 5. Spatial Distribution Map of East Java's regional GDP Growth 2020
Source: Data Processed, 2024

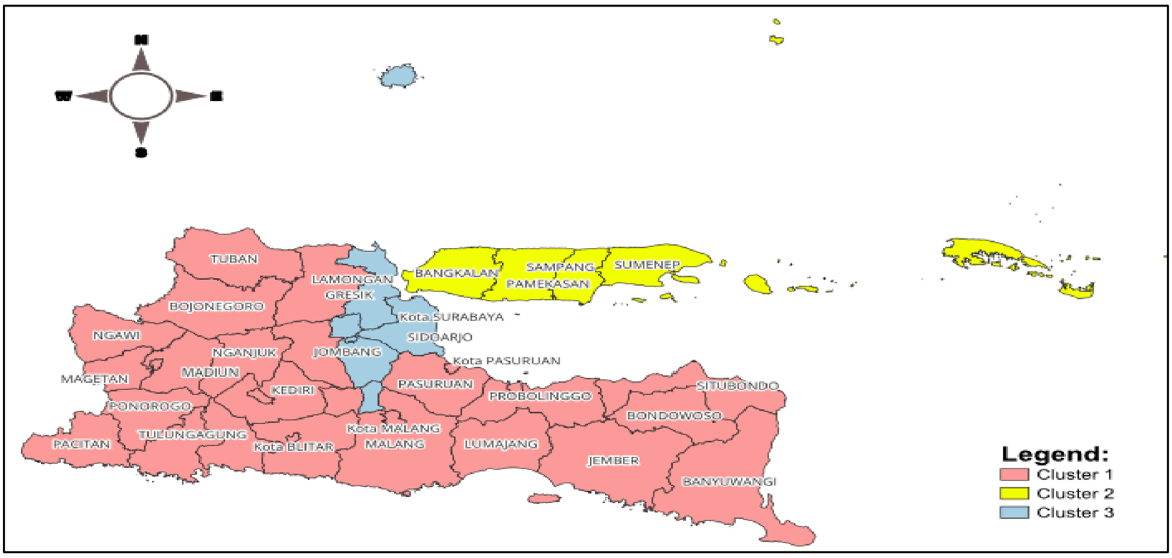


Figure 6. Spatial Contiguous Clusters of East Java's Regencies/Municipalities based on 2019 GGDP, HDI and Dens
Source: Data Processed, 2024

Table 2. The results of Moran's Test for 2019 East Java's GDP Growth with Customized Spatial weight Matrix and Queen Contiguity Spatial Weight Matrix

	GDP Growth 2019	
	Spatial Cluster – Customized Spatial Weight Matrix	**Queen Contiguity Spatial Weight Matrix**
I	0.6417	0.4168
$E(I)$	-0.02703	-0.02703
$var(I)$	0.002797	0.0135327
Z	12.643	3.815
p-value	2.2×10^{-16}	6.8×10^{-5}

Source: Data Processed, 2024

To analyze the spatial autocorrelation of 2019 GDP growth, Moran's test was conducted using both the customized spatial weight matrix and the traditional contiguity-based spatial weight matrix. The results, presented in figure 7, indicate significant spatial autocorrelation for 2019 GDP growth using both matrices. However, the customized spatial weight matrix yielded a much smaller p-value, indicating a stronger and more significant spatial autocorrelation. This result highlights the effectiveness of the customized spatial weight matrix in capturing the spatial interaction patterns of economic growth.

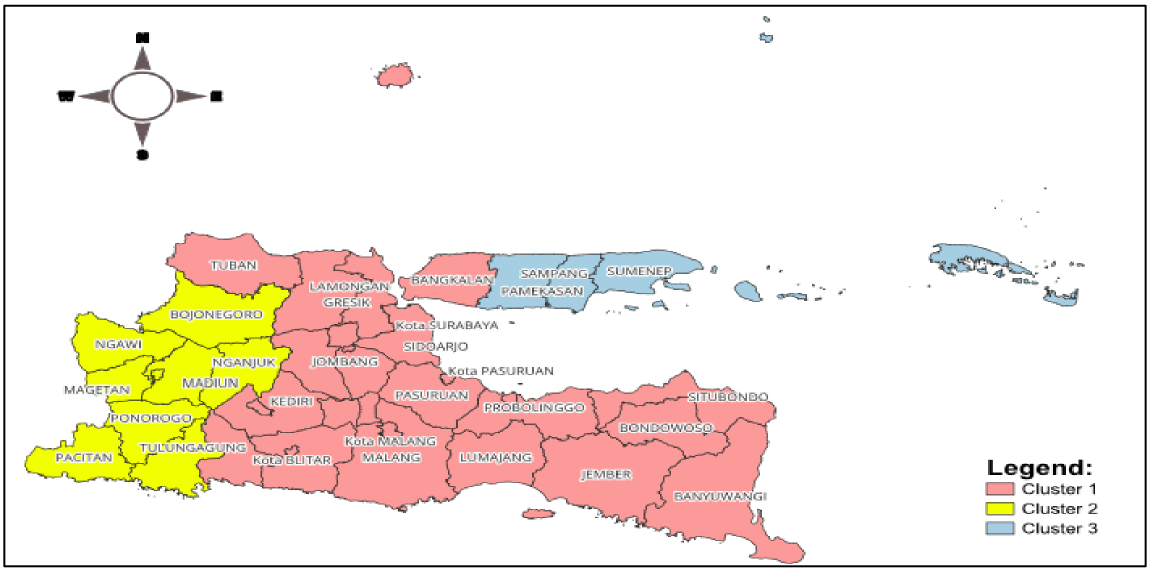


Figure 7. Spatial Contiguous Clusters of East Java's Regencies/Municipalities based on 2020 GGDP and HDI
Source: Data Processed, 2024

The spatial configuration of these clusters differs from those derived from the 2019 data, reflecting variations in the underlying spatial relationships. Moran's test, conducted using the customized spatial weight matrix based on these clusters, reveals significant spatial autocorrelation of GDP growth, with a p-value of 0.099 at the 10% level of significance. In contrast, when the test is based on the traditional contiguity-based spatial weight matrix, spatial autocorrelation is not detected, as indicated by a much higher p-value of 0.7965. The detailed results of Moran's test for both types of spatial weight matrices are presented in table 3 underscoring the advantage of the customized spatial weight matrix in identifying spatial interaction patterns for GDP growth.

Table 3. The results of Moran's Test for 2020 East Java's GDP Growth with Customized Spatial weight Matrix and Queen Contiguity Spatial Weight Matrix

	GDP Growth 2020	
	Spatial Cluster – Customized Spatial Weight Matrix	**Queen Contiguity Spatial Weight Matrix**
I	0.2296	-0.13406
$E(I)$	-0.02703	-0.02703
$var(I)$	0.003617	0.01679
Z	4.2668	-0.82604
p-value	0.099	0.7965

Source: Data Processed, 2024

Using HDI and Dens from the 2021 data, the formation of spatially contiguous clusters is shown in Figure 8. These clusters were used to construct the customized spatial weight matrix for analyzing the spatial autocorrelation of 2021 GDP growth. Moran's test was performed using both the Spatial Clusters-Customized Spatial Weight Matrix and the traditional contiguity-based spatial weight matrix, with the results summarized in Table 4. The p-values from the tests indicate that both spatial weight matrices detect significant spatial autocorrelation in GDP growth. However, the test using the customized spatial weight matrix produced a smaller p-value, suggesting a stronger and more significant spatial autocorrelation. This finding highlights the effectiveness of the customized spatial weight matrix in better capturing the spatial interaction patterns of GDP growth for 2021.

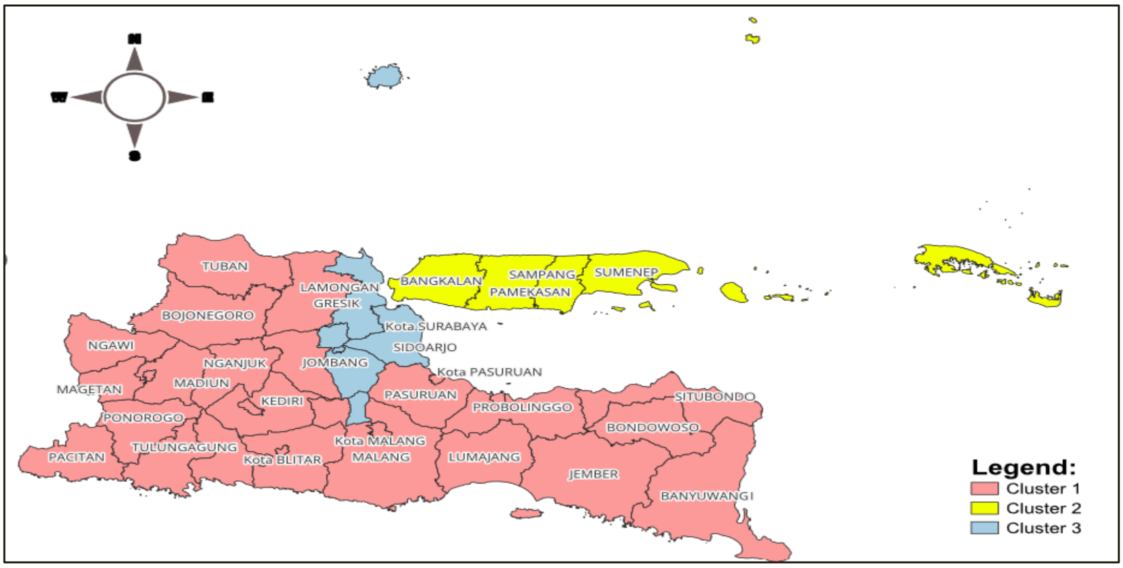


Figure 8. Spatial Contiguous Clusters of East Java's Regencies/Municipalities based on 2021 GGDP and HDI
Source: Data Processed, 2024

Table 4. The results of Moran's Test for 2021 East Java's GDP Growth with Customized Spatial weight Matrix and Queen Contiguity Spatial Weight Matrix

	GDP Growth 2021	
	Spatial Cluster – Customized Spatial Weight Matrix	**Queen Contiguity Spatial Weight Matrix**
I	0.09833	0.22187
$E(I)$	-0.02703	-0.02703
$var(I)$	0.002274	0.01107
Z	2.6285	2.3658
p-value	0.004288	0.008995

Source: Data Processed, 2024

The findings from this study highlight the importance of moving beyond traditional contiguity-based spatial weight matrices to more nuanced, cluster-based approaches. The results reveal that GDP growth in East Java's regencies/municipalities is influenced not only by the economic performance of immediate neighbors but also by regions within the same socio-economically and geographically informed clusters. This broader perspective on spatial dependencies provides critical insights into regional interactions and highlights several actionable policy implications for regional development.

The spatial clusters derived from the SKATER algorithm offer a framework for designing effective regional policies. By identifying regions with shared characteristics and interdependencies, policymakers can implement targeted strategies that address specific regional challenges and opportunities. This cluster-based approach is particularly relevant in contexts like East Java, where socio-economic disparities and uneven development remain significant challenges.

The findings emphasize the need for regional policies that consider the broader spatial dynamics of economic growth. Regions with significant disparities between economic output and socio-economic development can benefit from targeted support to enhance human capital and infrastructure. For example, policies that invest in education and healthcare in regions with high GDP growth but low HDI can create a more sustainable growth trajectory. Similarly, densely populated areas with stagnant growth may require strategic infrastructure investments to unlock economic potential.

CONCLUSION

This study demonstrates the value of incorporating spatial clustering into spatial weight matrix formation, providing a more nuanced understanding of spatial interactions in economic growth. The application of the SKATER algorithm to East Java's GDP growth data (2019–2021) successfully forms spatially contiguous clusters, reflecting both geographic proximity and socio-economic similarity. Moran's test results indicate that the customized spatial weight matrix captures stronger and more significant spatial autocorrelation compared to the traditional contiguity-based matrix. This highlights that spatial interactions extend beyond neighboring regions to include those within the same cluster, offering a robust framework for regional economic analysis.

While the approach proves effective, limitations include the use of only three years of data, a limited set of variables (GDP growth, HDI, and population density), and a focus on East Java, limiting generalizability. Future research could address these by incorporating additional variables that capture cultural, institutional, or environmental dimensions, exploring alternative clustering techniques that account for temporal dynamics, and conducting longitudinal analyses to examine how spatial interactions evolve over time and their impact on long-term development outcomes. By addressing these areas, future studies can refine this approach and enhance its applicability to broader contexts.

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