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Research Paper

Spatial Data Science for Regional Pattern Analysis: Dynamic Time Warping-Based Clustering of East Java's Economic Indicators

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Abstract
Motivated by the need to better capture dynamic regional disparities, this study examines spatial and temporal development patterns in East Java, Indonesia, using spatial panel data from 2020 to 2023. A data-driven framework is proposed that integrates Principal Component Analysis (PCA) for dimensionality reduction, Dynamic Time Warping (DTW) for temporal similarity measurement, and spatially constrained clustering using the SKATER algorithm. PCA compresses multiple socio-economic indicators, GDP growth, GDP level, Human Development Index (HDI), and population density, into a unified development profile, enabling comparison of regional trajectories over time. DTW captures non-linear temporal alignment, while SKATER preserves spatial coherence in cluster formation. The resulting clusters are used to construct an endogenous spatial weight matrix that reflects functional regional relationships rather than purely geographic adjacency. Validation using Moran's I indicates stronger spatial autocorrelation compared to conventional contiguity-based weights, suggesting improved representation of spatial interaction. Four clusters reveal distinct development patterns and uneven regional trajectories. By integrating dimensionality reduction with temporal alignment and spatial clustering, the proposed approach extends dynamic spatial weighting toward a functional interpretation of regional dependence and offers a transferable framework for spatial data science and regional policy analysis.

Keywords
Dynamic Time Warping, Spatial Data Science, Spatial Temporal Clustering, Regional Development, East Java, Regional Economic Pattern

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1. INTRODUCTION

Accurately capturing spatial dependency and its dynamic nature is essential for understanding regional economic systems and informing effective development strategies. In regional contexts, economic changes in one area often influence others through interconnected networks of trade, infrastructure, labor markets, and resource flows. These spatial interactions reveal important patterns in growth, inequality, and resilience, while their temporal dimension reflects how regions adapt to policy shifts, external shocks, and evolving global trends. Spatial data science provides tools to analyze these complex relationships by integrating location-based data with temporal dynamics. Methods such as spatial panel analysis, clustering algorithms, and spatial autocorrelation measures enable researchers to uncover hidden patterns and better model regional processes. This integration is particularly relevant for identifying not only where change occurs, but also when and how it unfolds across geographic space. Recent advancements in spatial data science increasingly emphasize the need to move beyond static geographic boundaries toward dynamic spatial clustering that evolves alongside socio-economic processes (Masías H et al., 2024; Quintero et al., 2022). A critical component of this shift is the ability to rigorously balance spatial coherence with temporal similarity. Because traditional Euclidean distances often fail to capture complex, non-linear temporal dynamics between regions, Dynamic Time Warping (DTW) has emerged as an effective method for quantifying regional similarity based on synchronized temporal patterns rather than fixed states (Liu et al., 2023; Zheng et al., 2023). By capturing these temporal dynamics, researchers can construct endogenous spatial weight matrices that reflect functional connectivity rather than relying solely on exogenous geographic proximity (Qu et al., 2021; Shi and Lee, 2018; Zhang et al., 2025).

These methodological developments are particularly relevant for regions characterized by heterogeneous growth patterns and evolving spatial interactions. East Java, Indonesia, offers a compelling case for examining such spatial-temporal dynamics. As one of the country's key economic contributors, the province features a diverse mix of urban centers, industrial zones, and rural areas. Before the COVID-19 pandemic, East Java's economic growth consistently outperformed the national average. Although the province experienced a downturn in 2020, it recovered quickly, reaching 5.34% growth in 2022. East Java features dynamic urban centers like Surabaya City, Malang City and Kediri City , as well as a diverse mix of rural and industrial regions. The province's economy is characterized by strong infrastructure networks, manufacturing industries, agriculture, and trade, making it a critical hub for regional and national economic activities (Hardjoko et al., 2021). However, despite its consistent economic performance, regional disparities persist, with some areas lagging behind in development compared to the economic growth centers (Solihin et al., 2021). Economic growth in regions like Surabaya City or Malang City often has a spillover effect on surrounding areas, influencing infrastructure development, job creation, and investments (Atikah et al., 2021). Understanding how growth centers influence surrounding areas, and where such influences fail to reach, is critical for addressing these disparities. These spatial spillovers, as observed in East Java's urban centers (Fitriani et al., 2021), do not always extend evenly across regions, highlighting the urgency of understanding where influence spreads, where it does not reach, and why. East Java's case underscores the need for spatial temporal approaches to better capture the dynamics of regional growth and to design policies that address persistent disparities in a more targeted and equitable manner. Although East Java provides a rich empirical setting due to its heterogeneous economic structure and strong spatial interactions, the analytical framework developed in this study is methodologically transferable to other regions characterized by dynamic regional linkages and evolving economic trajectories.

In spatial modeling, such interactions are quantified using spatial autocorrelation measures that rely on a spatial weight matrix, an essential tool for defining relationships among regions. Traditionally, this matrix is built using static criteria such as geographic distance or adjacency (Anselin, 1988; Beenstock and Felsenstein, 2019). However, these exogenous definitions may overlook the actual socio-economic connections between regions (Getis and Aldstadt, 2004), particularly when those connections evolve over time or extend beyond neighboring boundaries. Yang et al. (2022), for instance, demonstrate that dynamic spatial clustering allows researchers to analyze evolving spatiotemporal distributions rather than static geographic snapshots, emphasizing iterative changes in spatial patterns over time. Such developments highlight the need for clustering strategies that maintain geographic interpretability while capturing temporal dynamics. This perspective aligns with functional regional frameworks in which economic linkages form networks that extend beyond administrative adjacency. Beyond structural proximity, functional connectivity perspectives further suggest that spatial systems operate as adaptive networks where interactions depend on flows of people, capital, or resources rather than purely geographic distance. Molné et al. (2023) highlight how multi-scale spatial network analysis can reveal evolving connectivity patterns within adaptive regional systems, reinforcing the importance of viewing spatial relationships as dynamic and functionally driven. Building on these developments, recent research on endogenous spatial weights further highlights that spatial relationships may be shaped by socio-economic interactions rather than purely geographic proximity, motivating the development of adaptive and time-varying weight matrices that evolve alongside regional dynamics (Qu et al., 2021; Shi and Lee, 2018; Zhang et al., 2025). Similar spatiotemporal perspectives have also been applied in studies examining evolving hotspot patterns and deformation processes, reinforcing the importance of incorporating temporal evolution when interpreting spatial structures (Eboy and Kemarau, 2023; Khakim et al., 2023).

To address these limitations, this study applies a dynamic spatial clustering approach to construct a data-driven spatial weight matrix that incorporates both spatial and temporal dimensions. Temporal similarities between regions are measured using DTW, while spatial clusters are formed using the SKATER (Spatial 'K'luster Analysis by Tree Edge Removal) algorithm (Assunção et al., 2006). This method groups regions with similar economic trajectories and characteristics, enabling the spatial weight matrix to reflect both local and non-local dependencies more accurately. Conceptually, this approach reframes spatial dependence as an emergent property of dynamic regional similarity rather than a fixed geographic structure, extending endogenous spatial modeling toward a functional interpretation of spatial interaction.

While recent studies have explored dynamic spatial clustering, DTW based similarity analysis, and endogenous spatial weight construction, these approaches are often developed separately. Dynamic clustering studies mainly focus on temporal similarity, whereas endogenous spatial weight research is usually framed within econometric models without integrating spatially constrained clustering. As a result, previous spatial–temporal studies rarely combine dimensionality reduction, temporal alignment, and spatially coherent clustering in a single framework for regional analysis. This study brings these components together to provide a data-driven way of defining spatial relationships based on evolving regional trajectories rather than fixed geographic assumptions. In this context, the novelty of this research lies in integrating Principal Component Analysis (PCA) based feature reduction, DTW similarity, and spatially constrained clustering to construct adaptive spatial weights that preserve spatial interpretability while capturing evolving economic trajectories. Using spatial panel data from 2020 to 2023, this study analyzes spatial interactions in East Java's economy that extend beyond contiguous borders. By redefining spatial dependency through dynamic clustering, the research aims to provide a more accurate representation of economic linkages across the province. The findings contribute to spatial data science by offering a replicable framework for regional analysis, and to regional economics by supporting evidence-based strategies for inclusive and sustainable development.

2. EXPERIMENTAL SECTION

2.1 Materials

This study focuses on 38 regencies and municipalities in East Java, Indonesia (see Figure 1 for the regional map), using spatial panel data covering the period from 2020 to 2023. The panel structure allows the analysis to capture both temporal variations and spatial interdependence in regional economic development. East Java comprises two main administrative categories: municipalities (*kota*) and regencies (*kabupaten*). In this study, municipalities are presented using the English term "City" to ensure consistency and readability for an international audience. The study area includes nine municipalities (City) and twenty-nine regencies, where regions without the "City" designation correspond to regencies.

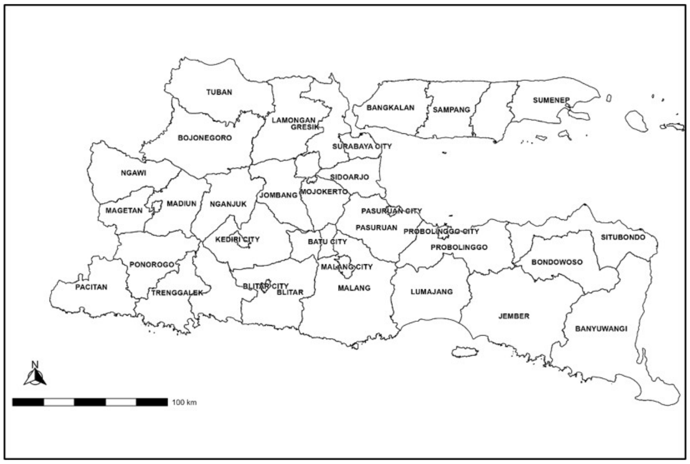

Figure 1. Map of 38 East Java's Regencies Municipalities

The dataset comprises a set of key indicators that reflect regional economic performance and social development. These include Gross Domestic Product growth (GGDP), GDP level, the Human Development Index (HDI), and population density (Dens). A summary of the variables used in the analysis is presented in Table 1.

The variables were selected based on their relevance to regional economic growth and their capacity to capture key dimensions of socio-economic development. GDP growth reflects short-term changes in economic performance, while GDP level indicates the overall economic scale of each region. HDI captures broader aspects of development, including education, health, and living standards. Population density represents demographic concentration, which influences infrastructure demand, labor markets, and spatial interactions. Together, these indicators provide a comprehensive framework for analyzing spatial and temporal patterns in East Java's regional economic development.

All variables were obtained from Badan Pusat Statistik (BPS), ensuring consistency in definitions and measurement across both spatial units and time periods. The resulting balanced panel dataset comprises 152 observations (38 regions across four years), providing a robust basis for spatial-temporal analysis and dynamic clustering.

2.2 Methods

This study adopts a dynamic spatial clustering framework to identify spatial and temporal patterns in regional economic development using spatial panel data. The approach integrates PCA for dimensionality reduction, DTW for measuring temporal similarity between regions, and the SKATER algorithm for forming spatially coherent clusters. By combining temporal alignment with spatial constraints, the framework provides a data-driven representation of regional relationships that extends beyond purely geographic adjacency.

This framework builds upon the approach proposed by Fitriani (2024), which demonstrated robustness in detecting meaningful spatial structures in spatial panel data. By combining time-aware similarity with spatial constraints, the method provides a data-driven foundation for identifying dynamic spatial clusters, enabling a more nuanced interpretation of regional economic patterns and disparities in East Java.

2.2.1 Formation of Dynamic Spatial Clusters from Multivariate Panel Data

Let n = 38 denote the number of regencies and municipalities in East Java, and T =4 the number of years from 2020 to 2023. For each year t, a data matrix is defined as:

$$X_t = \{x_{1t}, x_{2t}, \ldots, x_{38,t}\} = \begin{bmatrix} \mathrm{GGDP}_{1t} & \mathrm{GDP}_{1t} & \mathrm{HDI}_{1t} & \mathrm{Dens}_{1t} \\ \mathrm{GGDP}_{2t} & \mathrm{GDP}_{2t} & \mathrm{HDI}_{2t} & \mathrm{Dens}_{2t} \\ \vdots & \vdots & \vdots & \vdots \\ \mathrm{GGDP}_{38,t} & \mathrm{GDP}_{38,t} & \mathrm{HDI}_{38,t} & \mathrm{Dens}_{38,t} \end{bmatrix} \quad (1)$$

Each row represents a region, and each column corresponds to one of the four variables.

To obtain a compact representation of regional development, PCA is applied to each yearly data matrix X_t introduced in in Equation (1). The first principal component (PC1) is retained as it captures the dominant shared variance among the selected indicators. A vector of PC1 scores for year t is defined as:

$$\mathrm{PC1}_{1,t} = \begin{bmatrix} \mathrm{PC1}_{1,t} \\ \vdots \\ \mathrm{PC1}_{38,t} \end{bmatrix} \quad (2)$$

for t =2020,…,2023. The empirical interpretability of PC1 is later evaluated through its loading structure. For each region i, the sequence of PC1 scores derived in Equation (2) across years forms a univariate temporal profile:

$$Y_i = \{y_{i,2020}, \ldots, y_{i,2023}\} = \{\mathrm{PC1}_{i,2020}, \ldots, \mathrm{PC1}_{i,2023}\} \quad (3)$$

where $Y_i \in \mathbb{R}^T$ represents the compressed temporal development profile of region i, with $i = 1, \ldots, 38$.

Table 1. Economic Indicators Used in This Study

Indicator	Source
$GDP_{i,t}$: GDP growth of regency/municipality i at year t	Indonesian Central Bureau of Statistics (Badan Pusat Statistics – BPS Indonesia)
$GDP_{i,t}$: GDP of regency/municipality i at year t	
$HDI_{i,t}$: Human Development Index of regency/municipality i at year t	
$Dens_{i,t}$: Density of regency/municipality i at year t	

Note:
$i = 1, \ldots, 38$ refers to each regency/municipality and
$t = 2020, 2021, 2022, 2023$ denotes the year.

Temporal similarity between regional development trajectories is measured using DTW. It aligns time series by minimizing cumulative distance along an optimal warping path, allowing comparison even when similar patterns occur at different time points. This flexibility is particularly relevant for regional economic analysis, where development trajectories may evolve at different speeds across locations.

Unlike Euclidean distance or correlation based similarity, which assume synchronous observations, DTW captures structural similarity under temporal shifts. Recent methodological work shows that DTW based similarity measures can detect complex dynamic relationships more effectively than traditional metrics. Wiafe et al. (2025) demonstrate that normalized DTW improves sensitivity in identifying evolving temporal patterns, while Zhang et al. (2021) emphasize that weighting temporal components enhances similarity assessment in clustering tasks.

Based on the temporal profiles defined in Equation (3), Dynamic Time Warping (DTW) is employed to measure the non-linear temporal dissimilarity between each pair of regions i and j:

$$D_{ij}^{\mathrm{DTW}} = \mathrm{DTW}(Y_i, Y_j) \tag{4}$$

producing a symmetric $n \times n$ temporal distance matrix D^{DTW}. The use of PCA derived temproral profile prior to DTW follows the framework of Fitriani (2024), which showed that dimensionality reduction improves clustering stability while preserving dominant temporal structures.

Alternative distance metrics such as Euclidean distance, correlation-based similarity, and derivative-based measures were considered, however, these approaches assume linear temporal alignment and may fail to capture non-linear development dynamics. Because the temporal dimension in this study is relatively short (T=4), no explicit warping window constraint is imposed. In longer time-series applications, constraints such as the Sakoe–Chiba band are often used to limit excessive warping (Geler et al., 2022). Future research may explore constrained DTW or alternative similarity measures as part of a robustness assessment.

To ensure that clusters are geographically contiguous, the SKATER algorithm is applied to the DTW distance matrix under spatial constraints. A spatial graph is constructed where each node represents a region, and edges connect neighboring regions as defined by a first-order queen contiguity matrix. Each edge (i, j) is assigned a weight equal to D_{ij}^{DTW}, reflecting temporal dissimilarity. SKATER constructs a minimum spanning tree (MST) over this graph and partitions it by removing the $K - 1$ edges with the largest weights. This process forms K spatial clusters in which regions are both temporally similar (based on their compressed time series) and spatially connected (Assunção et al., 2006).

The number of clusters K is determined using the ratio of within-cluster sum of squares (SSW) to total sum of squares (SSTO). The optimal K is selected at the point where additional clusters produce diminishing reductions in the SSW/SSTO ratio, consistent with elbow-type cluster selection criteria (Modak, 2024). While stability-based validation measures have recently been proposed (Tarekegn et al., 2025), the present study prioritizes spatial interpretability and policy relevance within a constrained clustering framework.

2.2.2 Formation of Cluster-Based Spatial Weight Matrix

From the clustering output, a spatial weight matrix $W \in \mathbb{R}^{n\times n}$ is constructed such that:

$$w_{ij} = \begin{cases} 1, & \text{if regions } i \text{ and } j \text{ are within one cluster} \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

The matrix is row-standardized so that each row sums to one, ensuring comparability of spatial influence across regions and consistency with standard spatial econometric practice (Elhorst, 2014). Unlike traditional contiguity matrices, this cluster-based weight matrix reflects endogenous functional relationships derived from shared socio-economic trajectories.

2.2.3 Moran's I Test with Adjustment for Panel Setting

To evaluate the presence of spatial autocorrelation within the panel data framework, the spatial weight matrix W, whose element w_{ij} are defined in Equation (5), must be adapted to account for multiple time periods. This is done by constructing a panel version of spatial weight matrix using Kronecker product:

$$V = I_T \otimes W \tag{6}$$

where I_T is an identity matrix of size T.

The resulting matrix enables computation of a panel Moran's I statistic that captures cross-sectional spatial dependence across regions while preserving the temporal structure of the data (Elhorst, 2014; Lee and Yu, 2012). Temporal dependence is reflected in the repeated observations across time periods, whereas the Moran's I statistic specifically evaluates spatial interaction at each period of time.

2.2.4 Cluster Interpretation and Validation

The spatial weight matrix derived from dynamic clustering is validated using the global Moran's I statistic, confirming the presence of spatial autocorrelation within the panel dataset. Each cluster is interpreted based on average values and temporal trends of GDP growth, GDP level, HDI, and population density. Visualization tools such as thematic maps, time-series plots, and boxplots are used to support interpretation. These visualizations help identify distinctive cluster types, such as rapidly developing urban centers, lagging peripheral areas, or transitional rural-industrial regions.

Cluster compactness is evaluated through the SSW/SSTO ratio, which measures the reduction of unexplained variance achieved by clustering. The selected clustering solution demonstrates substantial reduction in within-cluster variation, supporting the coherence of the resulting regional groupings. Temporal trend analysis is presented as an exploratory descriptive tool to illustrate development trajectories rather than as formal hypothesis testing; future work may incorporate statistical comparison of functional trajectories to further validate inter-cluster differences.

3. RESULTS AND DISCUSSION

Across the study period, PC1 defined through the temporal profiles in Equation (3), explains approximately *55% – 63%* of total variance (see Table 2), indicating that it captures the dominant shared structure among indicators while preserving meaningful regional heterogeneity. Examination of PCA loadings, presented in Table 3, shows that HDI and population density consistently exhibit the largest absolute contributions to PC1 across all years, followed by GDP, while GGDP contributes relatively less. The stability of loading magnitudes suggests that PC1 captures a composite development profile reflecting structural socio-economic conditions rather than short-term growth fluctuations. Differences in loading signs across years are expected due to the rotational indeterminacy of PCA and do not affect interpretation.

Building on this dimensionality reduction, the study applies a dynamic spatial clustering approach to East Java's economic indicators (2020–2023), capturing both spatial and temporal dimensions in the formation of clusters. The distance between each pair of regions is calculated using the DTW based dissimilarity cost defined in Equation (4). The selection of the optimal number of clusters (K) was guided by the SSW to SSTO ratio, which evaluates how well the clustering structure reduces unexplained variance. As shown in Figure 2, the ratio declines significantly until four clusters (K =4), beyond which additional clusters yield diminishing returns. This supports

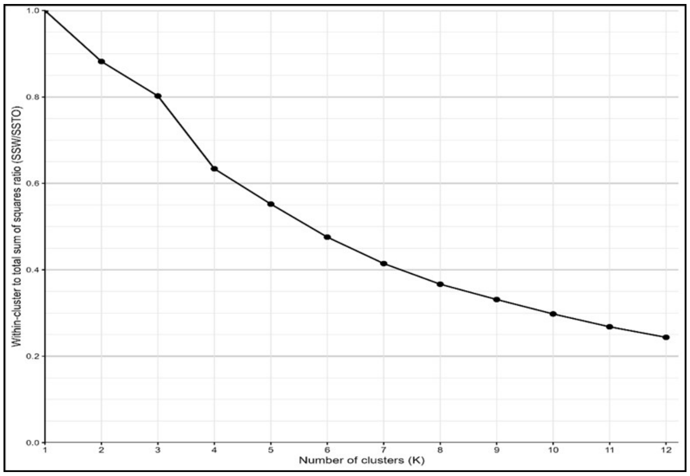

Figure 2. The Ratio of SSW to SSTO by Number of Cluster

Table 2. Proportion of Total Variance Explained by the First Principal Component (PC1) for Each Year (2020–2023)

Year	Percent Variance Explained by 1st PC (PC1)
2020	63.46
2021	57.79
2022	58.55
2023	55.34

Table 3. Loadings of the First Principal Component (PC1) Across Variables and Years (2020–2023)

Year	Variable	Loading of 1st PC (PC1)
2020	GGDP	-0.4476
	GDP	0.4654
	HDI	0.5366
	Dens	0.5433
2021	GGDP	0.3370
	GDP	0.4269
	HDI	0.6064
	Dens	0.5801
2022	GGDP	-0.3529
	GDP	-0.4296
	HDI	-0.6017
	Dens	-0.5735
2023	GGDP	0.1843
	GDP	0.4535
	HDI	0.6292
	Dens	0.6037

the use of four spatial clusters as a compact and interpretable grouping that balances parsimony and explanatory power.

To assess whether the clustering structure captures spatial dependency effectively, the Moran's I was computed using the cluster-derived spatial weight matrix defined in Equation (6). Results in Table 4 indicate significant spatial autocorrelation across all four indicators, GRDP growth, GDP, HDI, and population density, with highly significant p values. These results confirm that regions grouped via dynamic clustering share meaningful spatial relationships, even when they are not geographically adjacent. Comparatively, Moran's I values based on the conventional queen contiguity matrix showed weaker or non-significant autocorrelation for GDP and density. This highlights the advantage of a data-driven spatial structure: while traditional adjacency may overlook functional connections between distant but economically similar areas, dynamic clustering reveals those links through shared development profiles.

Table 4. The Result of the Moran's I test for All Indicators Under Cluster-Based and Queen Contiguity Spatial Weights

Variable	p value of Moran's I Test	
	Cluster-Based Spatial Weight	Queen Contiguity Spatial Weight
GDP Growth	5.26×10^{-104}	5.09×10^{-26}
GDP	1.15×10^{-4}	0.296
HDI	1.77×10^{-25}	2.14×10^{-7}
Density	6.40×10^{-6}	0.334

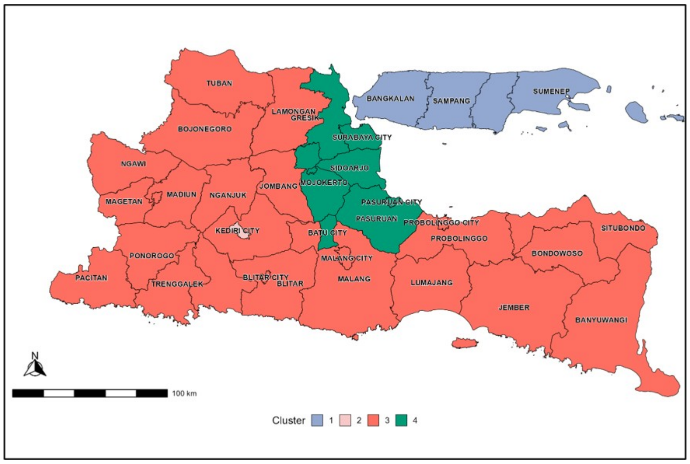

Figure 3. Map of East Java Regencies Municipalities by Clusters

While alternative endogenous spatial weights such as economic-distance or network-based matrices have been discussed in the literature, the present study focuses on evaluating the proposed cluster-based structure relative to conventional queen contiguity weights, rather than to compare a wide range of alternative weighting schemes. The comparison is intended to demonstrate the value of data-driven spatial relationships rather than to provide a comprehensive evaluation of all possible weighting schemes.

These findings reinforce the argument raised in the introduction: static spatial weights based solely on geographic proximity may fail to capture evolving and non-local economic interactions. By redefining spatial dependency through dynamic clustering, the analysis provides a more functionally grounded representation of interregional linkages.

The resulting four-cluster configuration in Figure 3 demonstrates spatial coherence and meaningful differentiation in economic profiles. Clusters capture both contiguous and non-contiguous groupings, reflecting the complexity of East Java's regional economy. The characteristics of each cluster are summarized in Table 5, which outlines the regional composition and general trends in GDP growth, GDP, HDI, and population density. These descriptive profiles provide a foundation for interpreting the spatial and socio-economic roles of each cluster. Rather than relying solely on administrative classifications, cluster interpretation is grounded in the observed statistical profiles of these indicators.

Drawing on the information in Table 5, each of the four clusters can be characterized by their shared socio-economic patterns as follows:

- **Cluster 1** corresponds to Madura Island regions, characterized by lower HDI and relatively modest economic performance. The consistency of this grouping across time suggests persistent structural disparities that differentiate it from other parts of East Java.
- **Cluster 2** consists solely of Kediri City and stands out with consistently high GDP, HDI, and population density. Its separation from other regions reflects a distinct development profile characterized by strong economic scale and human development outcomes.
- **Cluster 3** represents a large group of regions characterized by average GDP levels, moderately low to improving HDI, and relatively low population density. These regions exhibit moderate development dynamics and reflect transitional economic structures where growth is steady but uneven. The inclusion of several municipalities within this cluster indicates that administrative status alone does not determine development patterns.
- **Cluster 4** captures an urban industrial corridor, including regions such as Surabaya City, Sidoarjo, and surrounding municipalities. This cluster shows moderate to moderately high GDP levels and relatively stable development trajectories, reflecting strong economic integration and infrastructure connectivity.

While spatial clustering reveals structural disparities, incorporating temporal dynamics allows the model to capture how regional conditions evolve over time. This enables the identification of regions with parallel development patterns regardless of physical proximity and strengthens the interpretation of socio-economic change from a data-driven perspective. Figure 4 displays the temporal trends of four key socio-economic in-

Table 5. Socio-Economic Characteristics and Members of Each Cluster

Cluster	Regions	GDP Growth	GDP	HDI	Density
1	Bangkalan, Pamekasan, Sampang, Sumenep	Low to Moderate	Moderately Low Average	Low (stable)	Average (stable)
2	Kediri City	Low to Average	High (stable)	High (stable)	High (stable)
3	Banyuwangi, Blitar, Bojonegoro, Bondowoso, Jember, Jombang, Kediri, Blitar City, Madiun City, Malang City, Probolinggo City, Lamongan, Lumajang, Madiun, Magetan, Malang, Nganjuk, Ngawi, Pacitan, Ponorogo, Probolinggo, Situbondo, Trenggalek, Tuban, Tulungagung	Moderate to Moderately High	Average (stable)	Moderately Low to Average	Moderately Slow
4	Gresik, Batu City, Mojokerto City, Pasuruan City, Surabaya City, Mojokerto, Pasuruan, Sidoarjo	Moderate to Moderately High	Average to Moderately High	Moderately Low to Average	Average (stable)

dicators, GDP growth, GDP, HDI and population density, for each of the five dynamic clusters over the 2020–2023 period.

Based on the trajectories shown in Figure 4, HDI increased steadily across all clusters, although disparities remain evident. Cluster 2 consistently recorded the highest human development levels, while Cluster 1 remained at the lowest end of the spectrum. GDP growth indicates a strong post-pandemic recovery across most clusters, particularly Clusters 3 and 4, whereas Cluster 2 exhibited more moderate growth despite its high baseline. GDP levels show a strong concentration of economic activity in Cluster 2, while Cluster 4 represents a secondary economic corridor with consistently moderate-to-high output. Population density remains highest in Cluster 2, followed by moderate levels in Cluster 4, while Clusters 3 and 1 exhibit relatively lower and more stable density patterns.

The temporal patterns observed here are presented as descriptive evidence supporting the clustering structure rather than as formal statistical comparisons. Because the primary objective of the study is to construct dynamic spatial weights through clustering, the trend analysis is intended to illustrate how development patterns evolve within clusters rather than to test inter-cluster differences statistically.

The dynamic spatial clustering framework developed in this study provides policy insights that go beyond traditional geographically defined regions by identifying areas that share similar socio-economic evolution patterns. Because the cluster-based spatial weight matrix reflects functional economic relationships rather than fixed administrative proximity, the resulting policy implications emphasize coordination among regions with comparable development profiles, even when they are not spatially adjacent.

First, the identification of a high-performing but relatively stable economic center, represented by Kediri City (Cluster 2), highlights the need for innovation-driven policies in mature regional economies. The dynamic spatial weights reveal that this region maintains strong structural indicators yet exhibits slower relative change over time. This suggests that policy focus should shift from basic development expansion toward technological upgrading, digital infrastructure, and creative-sector incentives that can generate new growth pathways while sustaining existing advantages.

Second, Cluster 1 (Madura Island) consistently displays lower HDI and moderate economic performance, indicating structural development challenges. The cluster-based spatial weights show that these regions form a coherent functional group with similar temporal dynamics, supporting the design of integrated policy interventions rather than isolated local programs. Investments in education, healthcare, and transport infrastructure should therefore be coordinated across the cluster to improve accessibility and strengthen links with higher-performing economic areas.

Third, Cluster 3 represents a broad set of regions with moderate socio-economic indicators and gradual improvement over time. The data-driven clustering indicates that these areas share similar development profiles despite differences in administrative classification. Policies aimed at strengthening local value chains, supporting Small and Medium-sized Enterprises (SMEs), and expanding vocational training can help accelerate structural transformation. Importantly, the dynamic spatial weights suggest that collaboration among these regions should be guided by shared economic characteristics rather than traditional urban rural distinctions.

Fourth, Cluster 4 reflects an urban–industrial corridor characterized by relatively strong economic integration. Because the dynamic spatial weights capture functional linkages among these regions, policy strategies may emphasize coordinated in-

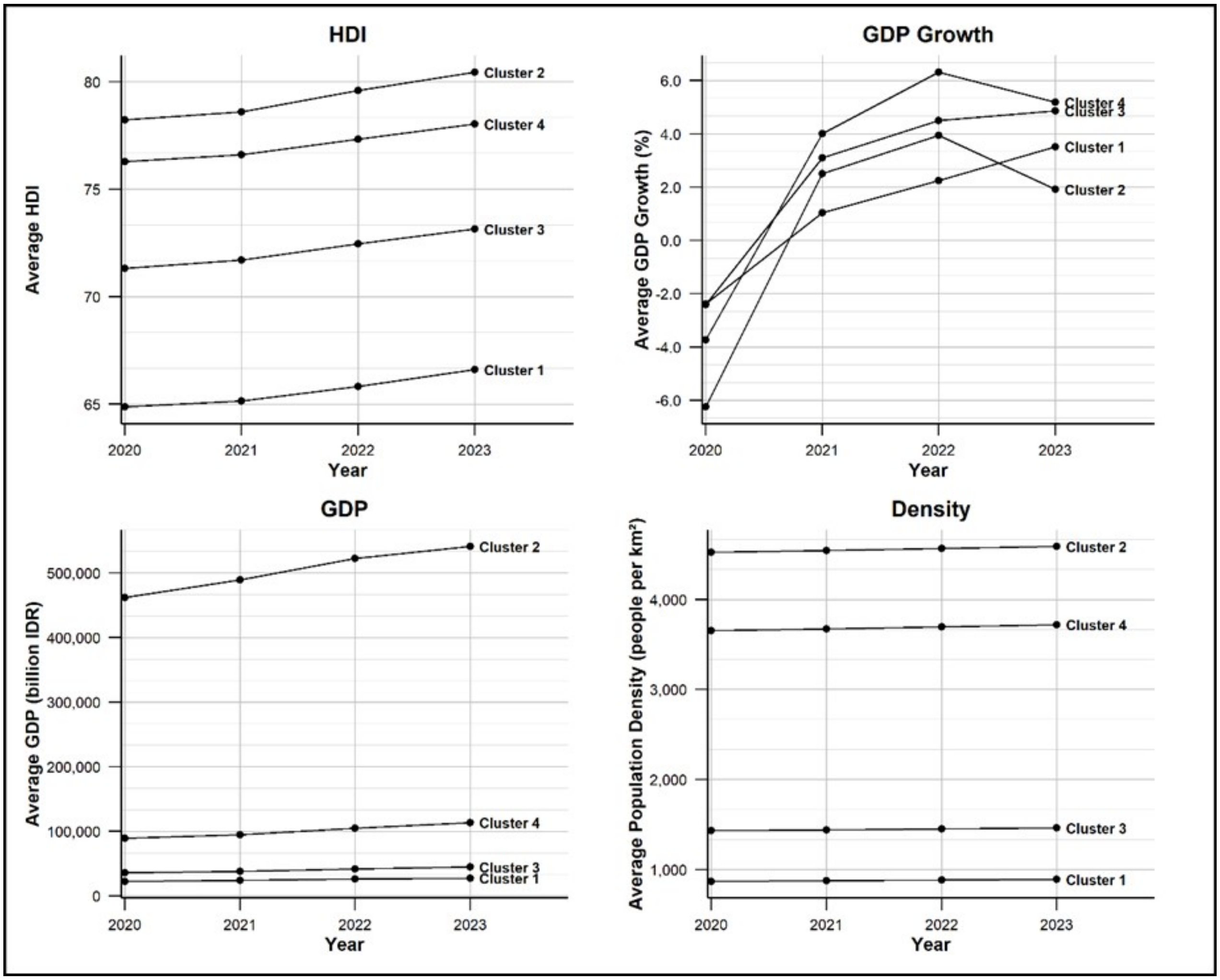

Figure 4. Temporal Trends of Average HDI, GDP Growth, GDP and Population Density by Cluster 2020 – 2023

frastructure development, logistics optimization, and regional innovation ecosystems. Strengthening cooperation across this cluster can enhance spillover effects and reinforce regional competitiveness.

More broadly, the findings demonstrate that regions with similar development trajectories are not always geographically contiguous. By redefining spatial relationships through dynamic clustering, the study provides a methodological basis for designing policies that operate across functional economic networks. This perspective encourages policymakers to move beyond administrative boundaries and instead prioritize coordinated planning among regions with aligned socio-economic dynamics.

4. CONCLUSIONS

This study highlights the importance of integrating spatial and temporal dimensions in regional economic analysis through a dynamic clustering framework. By combining PCA based feature reduction, Dynamic Time Warping (DTW), and the SKATER algorithm, the analysis identifies four clusters of East Java's regions that reflect statistically derived similarities in socio-economic indicators rather than predefined administrative categories. The resulting cluster based spatial weight matrix provides a data driven representation of spatial dependence, capturing stronger spatial autocorrelation than conventional contiguity based weights.

The findings reveal heterogeneous development patterns across clusters, particularly in GDP, HDI, and population density, and demonstrate how temporal similarity can uncover functional linkages among regions that are not necessarily geographically adjacent. Beyond methodological contribution, the proposed dynamic spatial weights offer a practical framework for understanding evolving regional interactions and informing more adaptive policy strategies.

Several limitations should be noted. The results depend on the selected indicators and the relatively short observation period (2020–2023), which may limit detection of long term structural changes. Future research could incorporate longer time horizons, additional variables, or alternative similarity measures to further evaluate the robustness and generalizability of the approach. Overall, this study shows how data driven spatial weight construction can enhance spatial data science by moving beyond static geographic assumptions toward adaptive representations of regional economic relationships.

5. ACKNOWLEDGMENT

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