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Spatial modeling of the open unemployment rate in West Java using eigenvector spatial filtering and spatially varying coefficients

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Abstract

Spatial modeling serves as a crucial approach in examining the Open Unemployment Rate (OUR) as it accommodates spatial dependence and regional heterogeneity. This study aims to model the OUR at the regency/city level in West Java Province for the 2020–2024 period using a spatial regression approach, by combining the Eigenvector Spatial Filtering (ESF) and Spatially Varying Coefficients (SVC) methods through the spmoran package in R. The ESF model is employed to reduce spatial autocorrelation in residuals by incorporating eigenvectors derived from a spatial weights matrix, while the SVC model captures local variations in the influence of explanatory variables on OUR across regions. The results reveal that the best-performing models based on Moran's I is ESF respectively, for each year. Several variables such as Gross Regional Domestic Product (GRDP) per capita at constant 2010 prices, number of poor people, and elevation were consistently significant and influenced regional variations in OUR. Spatial visualization of model predictions indicates a concentration of high OUR values in the northern and western regions of West Java, such as Bekasi City, Karawang Regency, and Depok City, while the southern and eastern regions, such as Pangandaran and Tasikmalaya Regencies, tended to have lower OUR values. These findings underscore the importance of spatial-based policy interventions in the employment sector.

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INTRODUCTION

The Open Unemployment Rate (OUR) is a significant economic indicator that reflects the social welfare and economic condition of a region (Azhari et al., 2019). A high OUR not only indicates limited employment opportunities but also suggests deeper structural challenges such

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as access to education, workforce quality, and regional economic competitiveness (Ewing & Hamidi, 2015). In West Java Province, the distribution of OUR from 2020 to 2024 exhibits substantial variation among regencies and municipalities, indicating the influence of local and spatial factors on unemployment (Muawanah et al., 2020). These variations cannot be fully captured through standard descriptive or classical statistical approaches; rather, they require spatially informed analysis to uncover deeper insights into geographic interdependencies (Hartono et al., 2024).

Moreover, OUR plays a direct role in shaping national resilience (Wisnu Dwi Andriyanto & Ima Amaliah, 2024). Persistent high unemployment rates may undermine social stability, increase the risk of conflict, and diminish community support for development programs. In the context of national defense, spatial inequality in unemployment distribution—especially in a strategic region like West Java—can affect the effectiveness of territorial-based policy implementation (Surahman et al., 2023). As a strategic province, West Java holds a vital role in supporting Indonesia's economic defense, which is strongly linked to social stability and regional resilience. This study aims to identify the spatial factors influencing OUR in West Java's regencies and municipalities using spatial regression approaches such as Eigenvector Spatial Filtering (ESF), Non-Spatially Varying Coefficients (NVC), Spatially Varying Coefficients (SVC), and Spatially and Non-Spatially Varying Coefficients (SNVC) which are relevant for understanding spatial dynamics and their implications for regional security.

Spatial analysis has become a vital tool in economics and social sciences to understand geographical patterns in data. This approach allows researchers to detect spatial dependence, i.e., the influence of geographic proximity between regions, which is often missed by conventional regression models (LeSage & Pace, 2018). Spatial regression is an extension of linear regression that accounts for spatial autocorrelation among observational units, revealing hidden interregional linkages. Models such as ESF and SVC are valuable in capturing spatial patterns and local variations, offering essential insights into the distribution of OUR across West Java.

These spatial interdependencies have become more relevant due to advances in geospatial data and technologies. Geographic data processing allows for more comprehensive analyses of variable relationships across space (Brundage et al., 2014). Spatial analysis has been applied in many countries to study issues such as unemployment distribution, housing prices, and socio-economic indicators. For instance, studies on housing prices in Boston demonstrated strong spatial influence, and the use of the spmoran package in RStudio has enabled more accurate spatial analysis (LeSage & Fischer, 2016; Murakami & Griffith, 2020).

Moreover, spatial regression can capture both direct and indirect spillover effects from neighboring areas. For example, economic growth in one region may influence employment conditions in adjacent areas through job creation or increased labor demand (Griffith et al., 2022). Understanding these spillovers is crucial in the context of West Java, where industrial expansion in urban centers might affect employment dynamics in surrounding districts. Thus, spatial statistical analysis can serve as a key foundation for targeted government policies aimed at reducing unemployment more holistically (Purwaningsih et al., 2022).

Currently, a gap exists in the literature regarding the application of spatial analysis to OUR in West Java. Most existing studies are descriptive or rely on classical regression models that overlook complex spatial dynamics (Sriyakul et al., 2019; Syazali et al., 2019). Few have explored how spatial factors shape OUR, including economic spillovers and infrastructure disparities across regions. Some research has shown that the ESF method can effectively reduce spatial autocorrelation in residuals, improving model accuracy in spatially complex regions (Murakami & Griffith, 2015). Additionally, combining ESF with SVC enables more precise modeling of coefficient variation across regions, particularly in heterogeneous spatial data (Murakami, 2017a).

This study applies spatial regression modeling using the spmoran package in RStudio, which supports the implementation of ESF and SVC to fill the research gap. This approach aims to better capture the spatial complexities of OUR distribution in West Java by considering key variables such as GRDP, education level, and labor market conditions in each region. Other research has also introduced Multiscale Geographically Weighted Regression (MGWR) to address spatial variation at different scales, which is relevant in high-heterogeneity datasets(Fotheringham et al., 2017; Li & Fotheringham, 2020).

The primary objective of this research is to develop a spatial model that accurately identifies and analyzes the drivers of OUR variability in West Java. Through the integration of ESF and SVC, the study seeks not only to improve model precision but also to offer rich insights into regional socio-economic dynamics. The findings are expected to contribute meaningfully to the national literature on spatial unemployment analysis and serve as a scientific foundation for policymakers in designing more effective and region-specific employment strategies.

DATA AND METHOD

1. Study Area, Data Source and Research Tools

This study focuses on the province of West Java, Indonesia, consisting of 27 regencies and municipalities as spatial units of analysis. The study period spans from 2020 to 2024, covering five consecutive years of cross-sectional data. The primary data source is the Central Bureau of Statistics (BPS) https://www.bps.go.id/id, which provides official and consistent socio-economic indicators for each region. The response variable is the Open Unemployment Rate (OUR), measured annually by BPS for each administrative region. A set of explanatory variables is selected based on prior literature and data availability, encompassing dimensions of demography, economy, and geography. These include population, labor force, number of poor people, education attainment, GRDP per capita (at constant 2010 prices), and elevation. To accommodate spatial analysis, each region is geocoded using latitude and longitude coordinates, and spatial neighborhood relationships are defined using a queen contiguity spatial weights matrix.

All data processing, spatial modeling, and visualization were conducted using RStudio, specifically employing the spmoran package. This package offers flexible tools for estimating spatial regression models that integrate both spatial filtering and spatially varying coefficient frameworks (Murakami, 2017b). Supporting packages for data wrangling, spatial visualization, and diagnostic evaluation include sf, spdep, ggplot2, and tmap. Spatial weight matrices were constructed using spdep, and eigenvector-based filtering was implemented via meigen and esf functions in spmoran (Murakami, 2024).

2. Variables and Spatial Data Structure

Predictor variables in modelling the OUR are shown in Table 1.

Table 1. Predictor Variables for OUR Modelling

No	Descriptions	Code
1	Elevation	x_1
2	Distance to Provincial Capital	x_2

No	Descriptions	Code
3	Percentage of Poor Population	x_3
4	Number of Poor Population	x_4
5	Total Population	x_5
6	GRDP per Capita at Constant 2010 Prices	x_6
7	Number of Villages/Sub-districts with Health Facilities (Pharmacy)	x_7
8	Percentage of Population with Government Health Insurance (PBI)	x_8
9	Number of Large and Medium Industrial Companies	x_9
10	Number of Workers in Large and Medium Industrial Companies	x_{10}
11	Number of Micro and Small Industrial Companies	x_{11}
12	Number of Workers in Micro and Small Industrial Companies	x_{12}
13	Population Aged 15 Years and Over Working in Finance, Insurance, Education, and Health Sectors	x_{13}
14	Population Aged 15 Years and Over Working in Agriculture, Forestry, and Fisheries Sectors	x_{14}

3. Variables and Spatial Data Structure

To model the spatial variation and capture geographic dependence in the unemployment data, five spatial regression models from the spmoran package were employed:

Eigenvector Spatial Filtering (ESF)

A spatial filtering approach that introduces selected eigenvectors from a spatial weights matrix into a regression model to remove residual spatial autocorrelation (Fang et al., 2019). This method estimates:

$$y = X\beta + E\gamma + \varepsilon, \ \ \varepsilon \sim N(0, \sigma^2 I) \tag{1}$$

where E contains spatial eigenvectors derived from a centered weight matrix W, and γ are coefficients associated with those filters.

Random Effect ESF (RE-ESF)

A hierarchical extension of ESF where the coefficients of spatial filters are treated as random variables:

$$y = X\beta + E\gamma + \varepsilon, \quad \gamma \sim N\left(0, \sigma_\gamma^2 \Lambda(\alpha)\right) \ \ \varepsilon \sim N(0, \sigma^2 I). \tag{2}$$

This improves flexibility and avoids overfitting, especially when numerous eigenvectors are included.

Non-Spatially Varying Coefficients (NVC)

A semi-parametric model that allows regression coefficients to vary with the value of each predictor, but without spatial dependence:

$$y_i = \sum_{k=1}^{K} x_{i,k}\beta_{i,k} + f_{MC}(s_i) + \varepsilon_i, \qquad \beta_{i,k} = b_k + f(x_i, k). \tag{3}$$

The variation is explained entirely by the predictor variable's magnitude.

Spatially Varying Coefficients (SVC)

A spatial model where regression coefficients vary geographically:

$$y_i = \sum_{k=1}^{K} x_{i,k}\beta_{i,k} + f_{MC}(s_i) + \varepsilon_i, \qquad \beta_{i,k} = b_k + f_{MC,k}(s_i), \tag{4}$$

allowing the effect of each independent variable to shift by location sis_isi, capturing spatial heterogeneity.

Spatially and Non-Spatially Varying Coefficients (SNVC)

A hybrid model combining spatial and attribute-based variation:

$$y_i = \sum_{k=1}^{K} x_{i,k}\beta_{i,k} + f_{MC}(s_i) + \varepsilon_i, \quad \beta_{i,k} = b_k + f_{MC,k}(s_i) + f(x_i, k). \tag{5}$$

This is the most flexible specification, ideal for datasets with complex spatial and non-linear effects.

4. Analytical Procedure

The analysis for each year from 2020 to 2024 follows a systematic workflow beginning with a multicollinearity assessment, where the Variance Inflation Factor (VIF) is calculated for all predictors and variables with VIF values exceeding 10 are removed to ensure model stability. Spatial eigenvectors are then generated using the meigen function, which computes eigenvectors from geographic coordinates and spatial weights, serving as essential components in ESF-based modeling. Subsequently, five spatial models: ESF, RE-ESF, NVC, SVC, and SNVC, are estimated using the spmoran package, with the OUR regressed on selected explanatory variables and spatial components; model performance is evaluated using Moran's I on residuals, where a value closest to zero indicates effective mitigation of spatial autocorrelation.

Finally, model outputs are visualized by mapping the spatial distribution of predicted unemployment values using thematic color gradients, accompanied by a summary of significant explanatory variables and the direction of their effects to support substantive interpretation. Unlike conventional regression which may rely on AIC or RMSE, the evaluation in this study focuses exclusively on the Moran's I index to reflect the spatial performance of each model.

RESULTS AND DISCUSSIONS

1. Spatial Autocorrelation Evaluation (Moran's I)

The spatial autocorrelation of residuals was assessed using Moran's I statistics to evaluate the performance of five spatial regression models: ESF, RE-ESF, NVC, SVC, and SNVC, applied annually from 2020 to 2024. The results showed significant residual spatial autocorrelation in most models, confirming the necessity of incorporating spatial components when modeling unemployment in West Java. The interpretation of Moran's I follows common spatial statistics categorization (Nosek & Netrdová, 2017) in Table 2, and Moran's index values for each model and year are presented in Table 3.

Table 2. Moran's Index Categorization

Moran's I	Categorization
0.00–0.30	Weak
0.30–0.50	Moderate
0.50–0.70	Strong
>0.70	Very Strong

Table 3. Moran's I Values on Spatial Regression Model Residuals (2020–2024)

Year	Moran's Index				
	ESF	RE-ESF	NVC	SVC	SNVC
2020	0.299	0.548	0.548	0.611	0.632
2021	0.508	0.739	0.640	0.619	0.560
2022	0.851	0.930	0.930	0.885	0.919
2023	0.508	0.647	0.636	0.619	0.507
2024	0.299	0.806	0.806	0.519	0.570

Based on Table 3, the ESF model consistently produced the lowest Moran's I values, indicating a better fit with reduced spatial dependence. In contrast, the RE-ESF, NVC, SVC, and SNVC models yielded higher autocorrelation levels, especially in 2022, where all models showed "very strong" spatial correlation. The ESF model consistently achieved the lowest residual Moran's I across all five years, indicating it most effectively eliminated spatial dependence and provided the most reliable estimates of regional unemployment patterns (Kim et al., 2019). Therefore ESF is selected for further spatial interpretation.

The best spatial regression model was determined using Moran's I as the primary evaluation criterion to assess spatial autocorrelation in residuals. The ESF model consistently produced the lowest Moran's I values, particularly in 2020 and 2024, indicating that it was the most effective model in eliminating spatial dependence. As an example, the general regression equation of the 2022 ESF model is expressed as:

$$\widehat{OUR_i} = \beta_0+\beta_1 x_{1i} + \beta_4 x_{4i} + \beta_6 x_{6i} + \beta_8 x_{8i} + \beta_9 x_{9i} + \beta_{10} x_{10i} + \beta_{15} x_{15i} + \sum_{l=1}^{L} \gamma_l E_{li}. \tag{6}$$

Several predictor variables significantly influenced the Open Unemployment Rate. Variables such as x_6 (GRDP per capita) consistently appeared significant with a positive effect, suggesting that regions with higher GRDP may also experience elevated unemployment, potentially due to labor market saturation or skill mismatches. Meanwhile, x_1 (elevation), x_4 (number of poor people), x_8 (health facilities), x_{10} (number of large industries), and x_{15} (employment in agriculture/forestry/fisheries) frequently showed negative coefficients, indicating their potential role in reducing unemployment.

2. Significance and Direction of Spatial Coefficients

The significance of explanatory variables was assessed based on p-values (< 0.05) and the sign of regression coefficients for each model. A summary of significant variables and coefficient directions is presented for each year.

Table 4. Summary of Significant Variables and Coefficient Signs in Spatial Models

Year	Model	Significant Variables (p<0.05) &Coefficient Signs
2020	ESF	$x_4(+), x_8(-), x_{10}(-), x_{15}(-)$
	RE-ESF	$x_4(+), x_6(+), x_8(-), x_{15}(-)$
	NVC	$x_4(+), x_6(+), x_8(-), x_{15}(-)$
	SVC	$x_6(+)$
	SNVC	$x_6(+)$
2021	ESF	$x_6(+), x_{10}(-), x_{15}(-)$
	RE-ESF	$x_4(+), x_6(+), x_{10}(-), x_{15}(-)$
	NVC	$x_4(+), x_6(+), x_8(-), x_{10}(-), x_{15}(-)$
	SVC	$x_6(+)$
	SNVC	$x_6(+)$
2022	ESF	$x_1(+), x_4(+), x_6(+), x_8(-), x_9(+), x_{10}(-), x_{15}(-)$
	RE-ESF	$x_1(+), x_4(+), x_6(+), x_8(-), x_9(+), x_{10}(-), x_{15}(-)$
	NVC	$x_6(+), x_{10}(-), x_{15}(-)$
	SVC	$x_1(+), x_4(+), x_6(+), x_8(-), x_{10}(-), x_{15}(-)$
	SNVC	$x_6(+)$
2023	ESF	$x_1(+)$
	RE-ESF	$x_6(+)$
	NVC	$x_6(+), x_9(+)$
	SVC	$x_6(+), x_{10}(-), x_{15}(-)$
	SNVC	$x_6(+)$
2024	ESF	$x_1(+)$
	RE-ESF	$x_1(+)$
	NVC	$x_6(+), x_9(+)$
	SVC	$x_6(+)$
	SNVC	$x_6(+)$

GRDP per capita (x_6) emerged as the most consistently significant variable across all models and years, always showing a positive relationship with unemployment. This suggests that higher GRDP is paradoxically associated with higher unemployment, possibly due to urban saturation effects or job-market mismatch. Employment in agriculture, forestry, and fisheries (x_{15}) and number of large industries (x_{10}) frequently exhibited negative coefficients, indicating that their increase is associated with lower unemployment, particularly in rural regions. Models ESF and RE-ESF generally detected more significant predictors than SVC-based models, reflecting their stronger sensitivity to spatial variation. In 2020–2022, more variables were significant, while in 2023–2024, only a few predictors retained statistical significance. This reflects changing socio-economic dynamics across regions, potentially influenced by external shocks such as the COVID-19 pandemic.

3. Spatial Mapping and Interpretation of The Best Model (ESF)

Based on the Moran's I evaluation, the ESF model was selected as the best-performing model for spatial prediction. Spatial maps were generated to visualize both actual and predicted OUR values for 2020–2024. Figure 2 highlights the spatial disparities in unemployment across West Java. Southern regions such as Garut and Tasikmalaya consistently exhibited low predicted unemployment, marked in darker purple or blue. Northern urban areas like Bekasi, Karawang, and Depok consistently showed higher predicted unemployment, marked in yellow and orange. In 2022, a spike in predicted unemployment was observed in central and northern areas (including Bandung), likely reflecting prolonged post-pandemic economic disruptions.

The ESF model effectively captured these spatial variations. Its ability to reduce residual autocorrelation ensures reliable predictions and interpretable spatial patterns. These findings confirm that spatial modeling is essential in understanding regional unemployment and its policy implications. Spatial dependence in unemployment is evident across regions, especially in urban-industrial corridors. Ignoring this spatial structure would lead to biased conclusions. The consistent significance of GRDP (x_6) suggests that economic growth alone is insufficient to reduce unemployment unless accompanied by inclusive employment strategies. The spatial filtering approach (ESF) proves effective not only in statistical terms but also in offering policy-relevant visual diagnostics, aiding local governments in identifying priority areas. These findings can guide provincial and municipal policymakers in designing spatially targeted labor interventions, with a special focus on northern urban regions that remain persistently high in unemployment.

The spatial distribution of OUR showed a persistent pattern over time. Urban areas in the north and west (e.g., Bekasi, Karawang, and Depok) consistently exhibited high unemployment rates, while southern regions such as Garut, Tasikmalaya, and Pangandaran had consistently low rates. This spatial disparity emphasizes the need for regionally targeted employment policies, particularly in high-density, economically saturated urban areas.

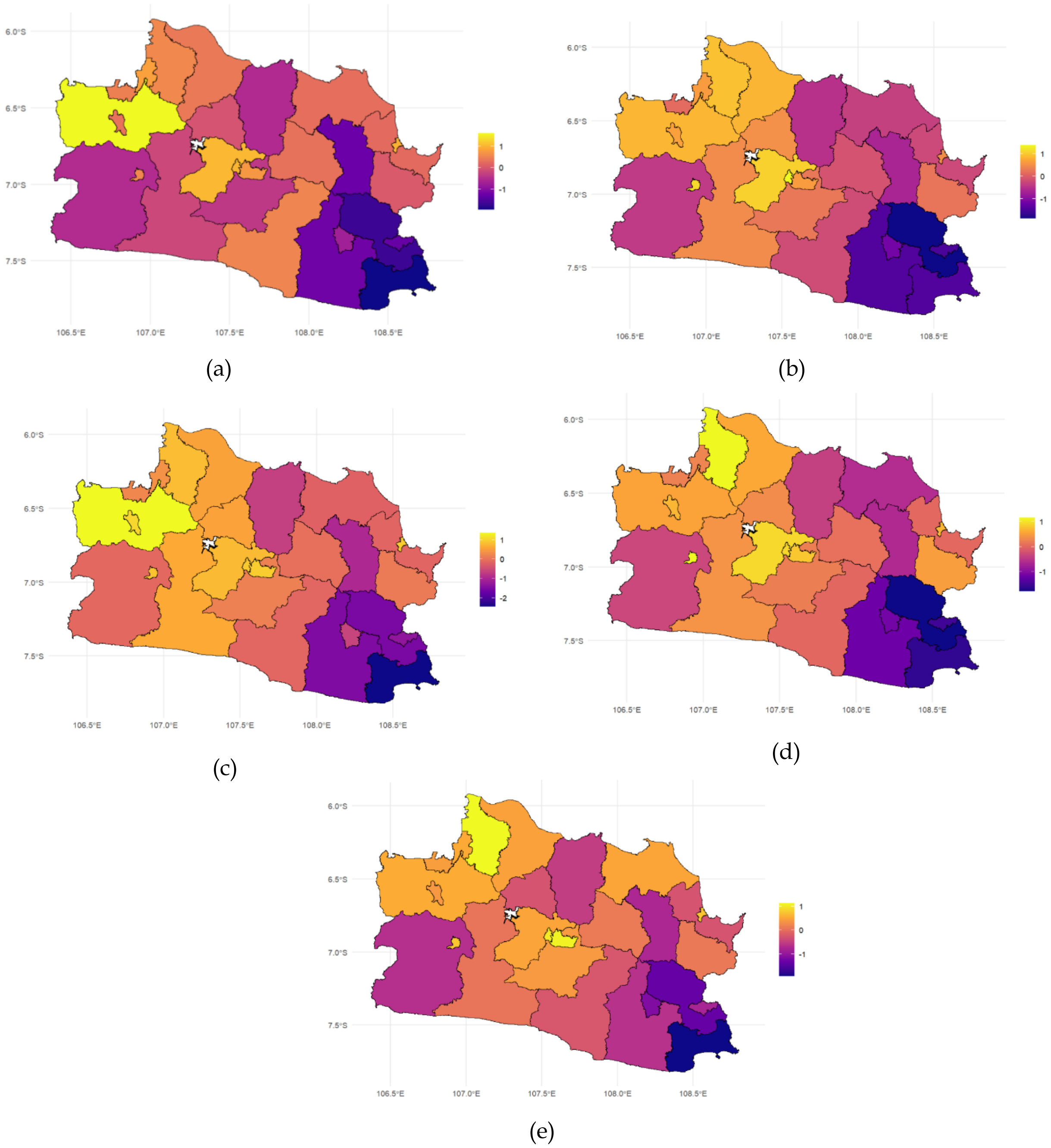

Figure 2. OUR Prediction using ESF Model in (a) 2020, (b) 2021, (c) 2022, (d) 2023 and (e) 2024.

CONCLUSION

This study developed and applied five spatial regression models—Eigenvector Spatial Filtering (ESF), Random Effects ESF (RE-ESF), Non-Spatially Varying Coefficients (NVC), Spatially Varying Coefficients (SVC), and Spatially and Non-Spatially Varying Coefficients (SNVC), to model the Open Unemployment Rate (OUR) in 27 regencies/municipalities in West Java Province from 2020 to 2024. The results of spatial modeling can be integrated into regional defense and development planning, especially in identifying labor vulnerability zones. Urban areas with high unemployment may present risks to social stability and economic resilience, which are critical aspects of national defense and regional security.

Further studies may explore and compare the performance of the SVC model with alternative methods such as Geographically Weighted Regression (GWR) or Multiscale GWR

(MGWR), particularly in capturing spatial heterogeneity across scales (Murakami et al., 2017). Since this study treats each year independently, future research can adopt spatio-temporal models (e.g., Spatio-Temporal ESF or ST-GWR) to assess how spatial relationships evolve over time and detect structural changes in regional unemployment patterns (Takele & Iticha, 2020). Future research may consider applying spatial machine learning techniques (e.g., Spatial Random Forest, Spatial Neural Network) to enhance predictive accuracy in modeling unemployment and explore complex non-linear spatial interactions (He et al., 2024; Zhu et al., 2024).

AUTHOR CONTRIBUTIONS

Each author of this article played an important role in the process of method conceptualization, simulation, and article writing.

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