Implementation of Spatial Autoregressive Analysis to Determine Factors Affecting the Population Dependency Ratio in West Sumatera

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ABSTRAK

Rasio ketergantungan penduduk menggambar beban yang ditanggung oleh penduduk usia produktif dalam menanggung kelompok usia nonproduktif. Penelitian ini menganalisis pola spasial rasio ketergantungan di kabupaten/kota Provinsi Sumatera Barat tahun 2024 menggunakan *Spatial Autoregressive Model* (SAR) sekaligus mengidentifikasi faktor-faktor yang memengaruhinya. Hasil menunjukkan bahwa *Total Fertility Rate* (TFR) dan *Median Age at First Marriage* (MAFM) secara signifikan meningkatkan rasio ketergantungan, sedangkan *Contraceptive Prevalence Rate* (CPR) dan proporsi penduduk lansia tidak signifikan secara statistik. Koefisien lag spasial yang positif dan signifikan ($\rho = 0.0852$) menunjukkan bahwa rasio ketergantungan yang lebih tinggi di wilayah tetangga berkontribusi terhadap peningkatan sebesar 8.52% pada rasio ketergantungan wilayah tertentu, menegaskan adanya efek spillover spasial. Pendekatan spasial juga mengungkap variasi antarwilayah, menunjukkan bahwa model SAR efektif menangkap pengaruh lokal maupun tetangga, sehingga memberikan pemahaman yang lebih akurat terhadap dinamika demografi. Temuan ini menekankan perlunya kebijakan yang tepat seperti pengendalian kelahiran, dan edukasi kesehatan reproduksi dengan mempertimbangkan interaksi antarwilayah untuk mengelola beban ketergantungan penduduk secara lebih efektif.

Kata kunci: Analisis Spasial; CPR; Fertilitas; MAFM; Rasio Ketergantungan; Spasial Lag; Sumatera Barat

ABSTRACT

The population dependency ratio illustrates the burden borne by the working-age population in supporting non-working-age groups. This study analyzes the spatial patterns of the dependency ratio across districts/cities in West Sumatra Province in 2024 using a Spatial Autoregressive Model (SAR) and simultaneously identifies the factors influencing it. The results show that Total Fertility Rate (TFR) and Median Age at First Marriage (MAFM) significantly increase the dependency ratio, whereas Contraceptive Prevalence Rate (CPR) and the proportion of elderly population are not statistically significant. The positive and significant spatial lag coefficient ($\rho = 0.0852$) indicates that higher dependency ratios in neighboring regions contribute to an 8.52% increase in a given region's dependency ratio, confirming the presence of spatial spillover effects. The spatial approach also reveals interregional variation, demonstrating that the SAR model effectively captures both local and neighboring influences, providing a more accurate understanding of demographic dynamics. These findings underscore the need for targeted policies such as fertility control, and reproductive health education considering interregional interactions to manage the population dependency burden more effectively.

Keywords: *CPR; Dependency Ratio; Fertility; MAFM; Lag Spatial; Spatial Analysis; West Sumatera.*

INTRODUCTION

The dependency ratio is an important indicator in population analysis because it reflects the burden of the productive age population in supporting the non-productive age population [1][2][3]. The higher the dependency ratio, the greater the pressure on the productive age group, namely people aged 15-64, to provide for the economic, social, and health needs of the younger and older age groups, namely those aged 0-14 and over 65 [4]. An increase in the dependency ratio indicates that the working-age population faces a heavier burden, as a portion of their income is not only allocated to meet their own needs but also to support the non-productive population, both those who have not yet entered the workforce and those who are no longer working [5]. This affects economic and social development, as well as regional policy planning.

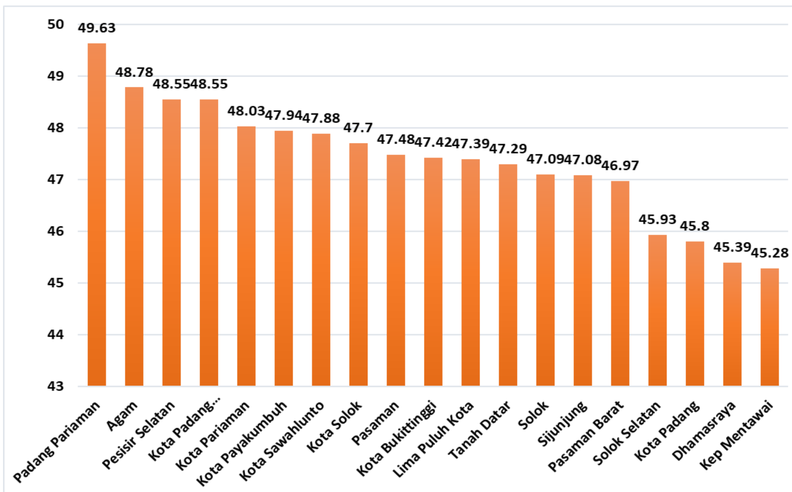


Figure 1. Dependency Ratio based on Regencies/Cities in West Sumatera in 2024

Based on the 2024 projections of the Central Statistics Agency, the dependency ratio in West Sumatera Province is 47.35, indicating that there are approximately 47 non-productive individuals for every 100 people of productive age. Figure 1 illustrates regional variations, with Padang Pariaman District recording the highest dependency ratio at 49.63, while the Mentawai Islands District exhibits the lowest at 45.28. These disparities reflect differences in demographic dynamics and age structures across districts and cities. One of the factors influencing changes in age structure is the Total Fertility Rate (TFR) [6]. The dependency ratio is influenced not only by the internal characteristics of a region but also by conditions in surrounding areas. This interregional linkage indicates the presence of spatial autocorrelation, whereby geographically adjacent regions tend to exhibit similar dependency ratio patterns. Such a condition implies that changes in the dependency ratio in a given district are significantly affected by the dependency ratios of neighboring districts. Consequently, classical approaches such as Ordinary Least Squares (OLS) regression are less appropriate, as they fail to account for spatial effects.

Spatial regression provides a more appropriate analytical framework as it is capable of capturing both intra-regional relationships and interregional interactions through the use of a spatial weight matrix [7]. When interregional interactions are defined by a combination of shared boundaries and vertex contiguity, the spatial weight matrix is constructed using the queen contiguity criterion, whereby regions are considered neighbors if they share either a common border or a vertex [8]. In empirical studies, two spatial regression models are most commonly applied: the Spatial Autoregressive (SAR) model, which incorporates spatial lags of the dependent variable, and the Spatial Error Model (SEM), which accounts for spatial correlation in the error term [7]. Given the limited number of empirical studies examining dependency ratios using spatial approaches in West Sumatera Province, this study employs the SAR model with a queen contiguity spatial weight matrix to explicitly capture spatial spillover effects across regions.

METHOD

Data and Variables

This study uses secondary data obtained from the BKKBN-managed website https://siperindu.online/, covering 19 administrative regions in West Sumatera Province in 2024 (12 districts and 7 cities). The response variable is the dependency ratio, while the predictor variables are defined as follows:

a. The Total Fertility Rate/TFR (X_1): the average number of children born to women of reproductive age (15–49 years).
b. The Contraceptive Prevalence Rate/CPR (X_2): the proportion of women aged 15–49 years using contraception.
c. The Median Age at First Marriage/MAFM (X_3): the median age at which women enter their first marriage.
d. The variable Proportion of Elderly/PE (X_4): the percentage of the population aged 60 years and above relative to the total population.

This study uses GeoDa as the software application to conduct spatial data analysis aimed at identifying the factors influencing the dependency ratio in West Sumatera Province. The spatial data consist of district-level shapefiles representing administrative boundaries of districts/cities, obtained from geosai.my.id.

Regression Analysis (OLS)

Linear regression is a statistical method used to analyze the relationship between predictor variables (X) and a response variable (Y). General form of linear regression models :

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \varepsilon$$

To ensure accurate estimates, the assumptions of normality, absence of multicollinearity, and homoskedasticity must be satisfied [9].

Spatial Regression

Spatial regression is used to examine the relationship between response variables and predictor variables while accounting for spatial effects across regions [10]. General form of models :

$$Y = \rho \boldsymbol{W} Y + X\beta + u$$
$$u = \lambda \boldsymbol{W} u + \varepsilon, \varepsilon \sim N(0, \sigma_\varepsilon^2, I_n)$$

In this case :

Y : response variable

X : predictor variable
ρ : spatial lag parameter coefficient of the response variable
$\boldsymbol{W}$: spatial weighting matrix
λ : spatial error parameter coefficient
$\boldsymbol{u}$: random error component that has a spatial effect
ε : random error component

Spatial Weight Matrix

The spatial weight matrix $\boldsymbol{W}$ is used to represent interactions between regions based on their spatial neighborhood structure [11]. Neighborhood relationships can be defined using rook contiguity (shared borders), bishop contiguity (corner adjacency), and queen contiguity (shared borders or corners).

The spatial weight matrix $\boldsymbol{W}$ can be defined as either standardized or non-standardized. In a row-standardized matrix, all neighboring regions are assigned equal weights such that the sum of each row equals one. In contrast, a non-standardized matrix assigns a value of one to neighboring regions and zero to non-neighboring regions. In this study, the spatial weight matrix is constructed using the Queen contiguity criterion, which captures a broader neighborhood structure by including regions that share either borders or vertices.

Moran's Index (I) test

Moran's Index (I) is used to identify the existence of global spatial dependence or correlation [11].

Moran's I test hypothesis:

$H_0 : I = 0$ (not spatial dependence)
$H_1 : I \neq 0$ (spatial dependence)

The test statistics used were :

$$Z(I) = \frac{E(I)}{\sqrt{VAR(I)}}$$

H_0 is rejected if the value $|Z(I)| > Z_{\alpha/2}$ or p-value $> \alpha$. Rejection of H_0 indicates that spatial autocorrelation between locations occurs.

Lagrange Multiplier test

The Lagrange Multiplier Lag test is conducted to examine the presence of spatial lag autocorrelation in the dependent variable [12].

Hypothesis for spatial dependency testing on lag:

$H_0 : \rho = 0$ (not spatial lag autocorrelation)
$H_1 : \rho \neq 0$ (spatial lag autocorrelation)

Hypothesis for spatial dependency testing on error:

$H_0 : \lambda = 0$ (not spatial error autocorrelation)
$H_1 : \lambda \neq 0$ (spatial error autocorrelation)

The test statistics used were :

$$LM = E^{-1}\left\{\left(R_y\right)^2 T_2 - 2R_yR_eT_1 + (R_e)^2(D + T_1)\right\} \sim X^2_{(m)}$$

Spatial Autoregressive Model (SAR)

Spatial regression is a method used to analyze the relationship between predictor variables and response variables by taking into account the spatial influences between different regions or locations [13]. One type of spatial modeling is spatial autoregressive, which occurs when $\rho \neq 0$ dan $\lambda = 0$. General form of models :

$$Y = \rho \boldsymbol{W} Y + X\beta + \varepsilon \text{ , } \varepsilon \sim (0, \sigma^2 I)$$

In this case :

Y : response variable

ρ : spatial lag parameter coefficient of the response variable

$\boldsymbol{W}$: spatial weighting matrix

β : parameter, which is the slope of the line

ε : random error component

Selection of the Best-Fitting Model

The selection of the best model is based on the model with the smallest AIC value, Akaike Info Criterion (AIC). The following is the equation for AIC [14] :

$$AIC = -2LogL + 2p$$

In this case :

L : Maximum likelihood value based on model estimation

p : Number of model parameters

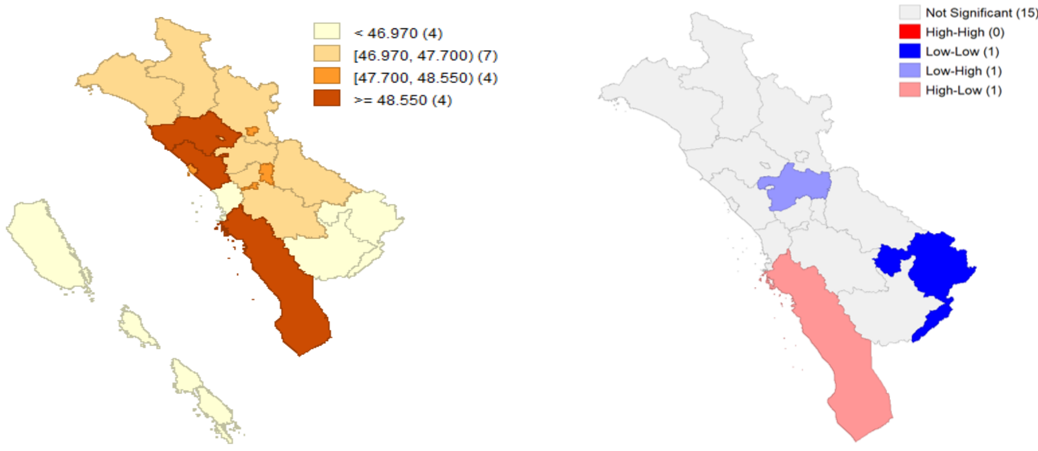
RESULT

The population dependency ratio averages 47.38, indicating that in 2024 approximately 47 individuals of non-working age are supported by every 100 working-age individuals in West Sumatera Province. As shown in Table 1, the lowest dependency ratio is observed in the Mentawai Islands (45.28), while the highest value is recorded in Padang Pariaman Regency (49.63).

Table 1. Descriptive Statistics

Variable	Mean	Std	Min	Max
Y	47.38	1.16	45.28	49.63
X_1	2.38	0.10	2.20	2.68
X_2	58.05	7.69	42.3	69
X_3	22.17	0.91	20.9	23.3
X_4	11.18	2.06	7.63	15.58

The population dependency ratio in West Sumatera Province is classified into four categories, namely very low, low, moderate, and high. As illustrated in Figure 2(a), the spatial distribution of the population dependency ratio exhibits a clustered pattern, indicating that regions with similar dependency ratio levels tend to be geographically concentrated.



(a) **(b)**

Figure 2. (a) Dependency Ratio in West Sumatera, 2024; **(b)** LISA Cluster Map

Figure 2(a) shows that the population dependency ratio in West Sumatera in 2024 varies across districts/cities and is classified into four value ranges: < 46.97, 46.97-47.70, 47.70-48.55, and ≥ 48.55. Dharmasraya Regency, Mentawai Islands, Padang City, and South Solok Regency fall into the lowest dependency ratio category < 46.97, indicating a dominance of the productive-age population and a relatively lighter burden in supporting the non-productive population. In contrast, Agam Regency, Padang Panjang City, South Pesisir Regency, and Padang Pariaman Regency are classified in the highest dependency ratio category ≥ 48.55, suggesting that each productive-age resident bears a heavier dependency burden compared to other regions.

Figure 2(b) shows the LISA map of the dependency ratio. Most districts and cities are not statistically significant, indicating weak local spatial autocorrelation. However, the presence of a Low–Low cluster and spatial outliers (Low-High and High-Low) suggests local spatial heterogeneity and interregional interactions, implying that dependency ratios are not spatially independent. The Mentawai Islands does not form a significant cluster due to its archipelagic location, which limits neighboring relationships under a contiguity-based spatial weight matrix, rendering it statistically insignificant despite its relatively low dependency ratio.

Linear Regression Modeling

The following is a model of population dependency ratio using a multiple linear regression model (OLS):

$$Y = 23.44 + 3.569X_1 - 0.020X_2 + 0.655X_3 + 0.185X_4$$

Table 2. Estimation of Linear Regression Parameters (OLS)

Variable	Coeff	p-value	Conclusion
intercept	23.4394	0.073	Not significant
X_1	3.56992	0.201	Not significant
X_2	-0.0201825	0.538	Not significant
X_3	0.655635	0.061	Not significant

X_4	0.185026	0.192	Not significant

Based on Table 2, the analysis results indicate that none of the predictor variables have a statistically significant effect on the population dependency ratio at the 5% significance level, with a coefficient of determination of 0.5128. However, the Median Age at First Marriage (MAFM) variable has a p-value that is close to the significance threshold, so it can be said to have a relatively greater effect on the variation in the dependency ratio than other variables.

Testing Spatial Autocorrelation

The Moran's I test is used to assess the presence of global spatial autocorrelation. As shown in Table 3, the test result indicates that spatial autocorrelation is not significant at the 5% significance level, suggesting the absence of global spatial autocorrelation.

Table 3. Moran's I test

Value	I
-1.5762	0.11498

Lagrange Multiplier test

The Lagrange Multiplier test shown in Table 4 shows that the Lagrange Multiplier (lag) is significant at the 5% significance level, indicating that the Spatial Autoregressive Model (SAR) is the most suitable model to use. Therefore, subsequent modeling will use the Spatial Autoregressive Model.

Table 4. Lagrange Multiplier test

Lagrange Multiplier	p-value	Conclusion
Lagrange Multiplier (lag)	0.00104	Significant
Robust LM (lag)	0.00053	Significant
Lagrange Multiplier (error)	0.05009	Not significant
Robust LM (error)	0.02405	Significant

Moran's I did not indicate significant global spatial autocorrelation at the 5% level, whereas the Lagrange Multiplier test was significant. This discrepancy arises from differences in function and sensitivity: Moran's I is a global exploratory measure that does not account for explanatory variables, making it less sensitive to conditional or moderate spatial dependence. In contrast, the Lagrange Multiplier test is model-based and calculated from linear regression residuals, making it more effective in detecting spatial dependence after controlling for explanatory variables. The significance of the agrange Multiplier test provides a strong and reliable indication of spatial effects, confirming that the Spatial Autoregressive (SAR) model is more appropriate than the Spatial Error Model (SEM). Both LM (lag) and Robust LM (lag) are highly significant, while LM (error) and Robust LM (error) are not significant, indicating that spatial lag effects dominate.

Spatial Autoregressive Modeling

The next step is to estimate the Spatial Autoregressive (SAR) model and conduct parameter estimation and hypothesis testing to identify statistically significant parameters.

Table 5. Estimation and Testing of Spatial Autoregressive Model Parameters

Variable	*Coeff*	*p-value*	Conclusion
ρ	0.0852	0.000	Significant
Konstanta	4.2844	0.569	Not significant
X_1	9.4878	0.000	Significant
X_2	-0.0248	0.157	Not significant
X_3	0.7912	0.000	Significant
X_4	0.0500	0.523	Not significant

Based on the SAR estimation results in Table 5, several important findings emerge regarding the factors influencing the population dependency ratio in West Sumatera. The spatial lag coefficient ρ = 0.0852 is positive and significant, indicating that an increase in the dependency ratio of neighboring regions raises the dependency ratio of a given region by 8.52% of the increase occurring in adjacent areas. This finding confirms the presence of strong spatial effects, suggesting that demographic pressures tend to form geographically clustered patterns.
Based on Table 5, the Spatial Autoregressive (SAR) model equation is obtained as follows:

$$\hat{y}_i = 4.28 + 0.0852 \sum_{j=1, i\neq j}^{19} w_{ij} y_j + 9.49X_1 - 0.024X_2 + 0.79X_3 + 0.05X_4$$

Among the demographic variables, the total fertility rate shows the largest positive coefficient of 9.49, indicating that a one-unit increase in TFR is associated with a 9.49% increase in the dependency ratio. The contraceptive prevalence rate has a negative coefficient of −0.024, suggesting that a 1% increase in contraceptive use is associated with a 0.024% decrease in the dependency ratio. The median age at first marriage exhibits a positive coefficient of 0.79, indicating that a one-year increase in MAFM is associated with a 0.79% increase in the dependency ratio. In addition, the proportion of elderly shows a positive effect, where a 1% increase in the elderly population is associated with a 0.05% increase in the dependency ratio.

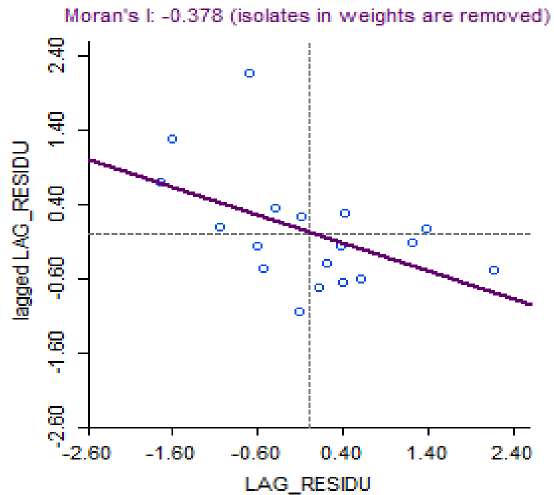


Figure 3. Moran's I Plot for The Residuals of The SAR

Meanwhile, the Breusch-Pagan test for heteroskedasticity yielded a value of 2.519 with a p-value of 0.641, indicating that there is no evidence of heteroskedasticity in the model, and that the assumption of constant variance is satisfied. After estimating the Spatial Autoregressive (SAR) model, Moran's I test was conducted on the residuals to evaluate the presence of spatial autocorrelation. The results indicate a Moran's I value of -0.378 with a p-value of 0.016. As the p-value is below the 5% significance level, the residuals still exhibit significant negative spatial autocorrelation, suggesting that the model has not fully accounted for spatial dependence and may require further refinement.

The Best-Fitting Model

Based on Table 6, the AIC value of the SAR model is lower than that of the linear regression model, indicating that the SAR model is more efficient and provides a better fit to the data. Therefore, the SAR model is the more appropriate choice, as it is able to capture spatial effects across regions that cannot be explained by the linear regression model.

Table 6. AIC dan R^2

Model	AIC	Log-likelihood	R^2
Linear Regression	54.837	-22.418	0.5128
Spatial Autoregressive (SAR)	39.909	-13.954	0.8004

The SAR model demonstrates substantially better performance than the linear regression model. It yields a lower AIC value, indicating a more efficient model fit, and a higher log-likelihood, suggesting stronger explanatory capability. Moreover, the SAR model achieves a markedly higher R^2 0.8004, showing that it explains a larger proportion of the variation in the dependency ratio. This confirms that incorporating spatial dependence significantly improves model accuracy compared to a standard linear approach.

DISCUSSION

The comparison between multiple linear regression (OLS) and the Spatial Autoregressive (SAR) model highlights the importance of explicitly accounting for spatial dependence in the analysis of the population dependency ratio in West Sumatra. The OLS model shows moderate explanatory power with an R^2 of 0.5128, whereas the SAR model substantially improves explanatory power to an R^2 of 0.8004. Additionally, the SAR model exhibits a lower AIC value 39.909 compared to 54.837 for OLS and a higher log-likelihood -13.954 compared to -22.418 for OLS, indicating that SAR is a more appropriate model and better captures the variation in the dependency ratio than the non-spatial linear regression. In the OLS model, none of the predictor variables are statistically significant at the 5% level, suggesting potential model misspecification due to the omission of spatial effects. In contrast, the SAR model identifies statistically significant effects for the spatial lag parameter, Total Fertility Rate (TFR), and Median Age at First Marriage (MAFM). The significance of the spatial autoregressive coefficient provides clear evidence of spatial spillover effects, indicating that changes in the dependency ratio in one district/city are influenced by conditions in neighboring districts/cities. The emergence of TFR and MAFM as significant predictors in the SAR model further indicates that fertility behavior and marriage patterns exhibit spatial clustering, which is not adequately captured by the non-spatial regression model.

Moreover, the positive effect of MAFM, although seemingly counterintuitive, is consistent with demographic transition theory. Higher MAFM is associated with delayed childbearing and persistently low fertility, which accelerates population aging. As the proportion of older individuals increases while the growth of the working-age population slows, the dependency ratio consequently rises. This indicates that the positive coefficient of MAFM reflects a shift in age structure toward an aging population rather than an increase in the number of young dependents. Additionally, the proportion of the elderly population shows the expected positive effect, with a 1% increase causing a 0.05% rise in the dependency ratio. However, a Moran's I test conducted on the residuals of the SAR model reveals a value of -0.378 with a p-value of 0.016, indicating significant negative spatial autocorrelation. This suggests that the SAR model has not fully accounted for all spatial dependencies, representing a limitation of the current model. Future research may consider refining the model or incorporating additional spatially relevant variables to better capture the complex spatial interactions affecting dependency ratios.

CONCLUSION

The results indicate the presence of spatial effects in the population dependency ratio in West Sumatra, suggesting that conditions in one area are influenced by surrounding regions. The SAR model shows that the Total Fertility Rate (TFR) and Median Age at First Marriage (MAFM) have positive and significant impacts on the dependency ratio, with higher fertility identified as the primary driver of population dependence. Meanwhile, the contraceptive prevalence rate and the proportion of elderly residents do not show significant effects. These findings suggest that interventions targeting fertility reduction such as strengthening family planning programs, improving access to reproductive health services, and providing education on responsible childbearing may be the most effective strategies to manage the dependency ratio. However, a Moran's I test on the SAR residuals indicates significant negative spatial autocorrelation, suggesting that the model has not fully accounted for all spatial dependencies and that the residuals violate the assumption of no spatial autocorrelation. This represents a limitation of the current model. This study only used cross-sectional data for the population dependency ratio across districts/cities in West Sumatra. Therefore, future research is recommended to extend the analysis using panel data, which would allow a more comprehensive understanding of both spatial and temporal dynamics of the dependency ratio. In addition, including additional spatially and socioeconomically relevant variables may further improve the explanatory power of the model.

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