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# SUR-SAR Modelling of the Human Development Index (HDI) of Regencies and Municipalities in West Java Province, Indonesia

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**Abstract** This study examines regional disparities in the Human Development Index (HDI) across 27 regencies and municipalities in West Java Province from 2022 to 2024 using a Spatial Seemingly Unrelated Regression–Spatial Autoregressive (SUR–SAR) model. To capture the multidimensional nature of development, the analysis integrates eight socio-economic determinants within a multi-equation system estimated via Maximum Likelihood. The study evaluates four model specifications, OLS, SUR, SAR, and SUR–SAR and explicitly compares spatial weight matrices. The diagnostic results reveal that the Economic Distance matrix significantly outperforms contiguity-based weights (Queen and Rook) in detecting spatial interactions. Consequently, the SUR–SAR specification utilizing Economic Distance emerges as the superior model, achieving the lowest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Empirical findings show that population density is the most robust positive driver of HDI, while poverty exerts a stable negative effect. Furthermore, the model uncovers structural nuances missed by classical approaches, Minimum Wage (LMW) becomes statistically significant only within the SUR–SAR framework, indicating strong wage-related spillover effects, while Inequality (GNR) exhibits a sign reversal from positive to negative, correcting for omitted variable bias present in non-spatial models. The significant positive spatial lag parameter across all years confirms that HDI improvements are spatially clustered, underscoring the necessity of coordinated regional policies over isolated interventions.

**Keywords** Spatial Econometrics, Seemingly Unrelated Regression (SUR), Spatial Autoregressive Model (SAR), SUR–SAR Model

**AMS 2010 subject classifications** 62M30, 91B82

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## 1. Introduction

Human development is a multidimensional policy objective that integrates improvements in health, education, and living standards into a single composite indicator, the Human Development Index (HDI). In West Java Province, one of Indonesia's most populous and economically dynamic regions, HDI values have shown steady improvement indicating gradual progress in overall human welfare. In 2024, the HDI of West Java Province reached 74.92, an increase of 0.53 points from the previous year, maintaining its status in the "high" development category. This improvement was driven by progress across all dimensions such as life expectancy rose to 74.92 years, expected years of schooling increased to 14.16 years, and mean years of schooling reached 9.37 years. In terms of living standards, the adjusted real per capita expenditure climbed to around IDR 13.23 million per year. However, disparities remain significant, with Depok City recording the highest HDI at approximately 83.69, while Cianjur Regency had the lowest at around 69.59, highlighting ongoing challenges in achieving equitable human development across West Java [40].

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However, the pace of this improvement remains uneven across regencies and municipalities, reflecting structural disparities in income opportunities, labor markets, educational attainment, and access to services. Such disparities are geographically patterned rather than random, as neighboring jurisdictions often share transport corridors, labor flows, supply chains, and social networks. Consequently, development outcomes in one area may be related to those in adjacent areas, suggesting that human development in West Java is spatially interconnected rather than independent. Despite continued progress, HDI inequality across regions persists, posing both empirical and methodological challenges. Empirically, differences in income distribution, education quality, and infrastructure investment produce enduring gaps between urbanized and rural areas. These patterns imply that HDI outcomes exhibit spatial dependence, whereby districts with similar socio-economic characteristics tend to cluster geographically [3, 46]. Moreover, HDI values across consecutive years are likely temporally correlated, given that the effects of provincial policies, economic growth, and demographic transitions evolve gradually. Classical linear regression models, which assume independently distributed errors, become inadequate under these conditions because they fail to account for cross-location and inter-year dependencies [26].

Although conventional Ordinary Least Squares (OLS) and single-equation Spatial Autoregressive (SAR) models have been widely employed in the analysis of regional Human Development Index (HDI) disparities, both approaches exhibit important methodological shortcomings. OLS estimators neglect spatial dependence among regions, which may lead to biased or inefficient estimates when spatial spillover effects are present [10, 49]. Single-equation SAR models partially address this limitation by explicitly modeling spatial interaction; however, they are typically estimated in a static framework and applied independently for each period, implicitly assuming temporal independence [15, 19]. As a consequence, intertemporal correlations arising from common structural shocks, persistent policy regimes, or long-standing regional characteristics are absorbed into the disturbance term and treated as statistical noise rather than as an intrinsic component of the development process [13, 42]. This separation between spatial dependence and temporal dynamics constitutes a clear methodological gap in the existing literature on regional human development.

To address these issues, this study employs a Spatial Seemingly Unrelated Regression – Spatial Autoregressive (SUR–SAR) framework that jointly captures spatial dependence among districts and cross-equation error correlation across multiple years. The theoretical foundations of this approach are drawn from two established econometric traditions. The Spatial Autoregressive (SAR) model explicitly incorporates spatial interactions in the dependent variable through a spatial weight matrix, recognizing that outcomes in one region may depend on those in neighboring regions [3, 35, 46]. The Seemingly Unrelated Regression (SUR) framework, introduced by Zellner [48] and further developed by Wickens [45], allows for contemporaneous correlations across related equations, enhancing efficiency and consistency in multi-equation estimation. Combining these two approaches yields the SUR–SAR model, estimated using Maximum Likelihood Estimation (MLE), which effectively captures both spatial and inter-year linkages within a unified inferential framework.

Recent advances in spatial econometrics increasingly stress the need to model multidimensional dependence structures that jointly account for spatial heterogeneity, temporal persistence, and parameter uncertainty. Methodological contributions published in recent years propose extensions of traditional Spatial Autoregressive (SAR) models that allow for heterogeneous spatial autocorrelation, time-varying coefficients, and distributional heterogeneity, often within Bayesian or semi-parametric frameworks [49, 36]. Parallel developments in spatio-temporal autoregressive modeling further demonstrate that integrating spatial and temporal dynamics substantially improves inference and predictive performance in regional and urban systems [9]. Despite these advances, much of the applied literature on Human Development Index (HDI) and related development indicators continues to rely on static or single-equation specifications that treat repeated regional observations as temporally independent [19]. As a result, contemporaneous correlations across time induced by persistent regional characteristics or shared structural shocks are rarely modeled explicitly. This gap indicates that empirical studies, particularly those focusing on subprovincial regions in developing countries have yet to fully adopt coherent system-based frameworks that simultaneously capture spatial spillovers and cross-time dependence.

Accordingly, this study has three aims within a clearly delimited scope. First, it specifies and estimates a SUR–SAR model for HDI across the 27 regencies and municipalities of West Java for the 2022, 2023, and 2024 periods, using a policy-relevant set of socio-economic predictors drawn from established determinants of human development. Second, it adopts Maximum Likelihood Estimation (MLE) as the estimation method to remain consistent with foundational spatial econometric practice and to ensure that cross-equation correlations are explicitly incorporated into the inferential process [3, 35, 45, 48]. Third, it positions the SUR–SAR model as an incremental yet meaningful methodological refinement over single-equation SAR or non-spatial SUR approaches commonly employed in regional HDI analysis in Indonesia.

The main contributions of this study can be summarized as follows. From a methodological perspective, the study advances regional HDI modeling by integrating spatial dependence and cross-equation correlation within a unified SUR–SAR framework, thereby addressing efficiency losses inherent in single-equation spatial models when intertemporal correlations are present. Empirically, the analysis provides evidence on how population density, poverty, wage structure, and other socio-economic factors are associated with HDI across West Java once spatial spillovers and shared temporal shocks are jointly accounted for. From a policy standpoint, the findings offer regionally grounded insights for provincial development planning by emphasizing the role of urban agglomeration effects and labor market conditions within an interconnected regional system, while also providing a replicable analytical template for future studies that seek to extend the framework to longer time horizons, alternative spatial weight matrices, or dynamic and Bayesian spatial specifications.

## 2. Methodology

This section describes the data and modeling framework used to analyze the HDI across the 27 regencies and municipalities of West Java Province for the 2022–2024 period. The empirical approach integrates spatial and temporal dependencies using a SUR–SAR framework estimated by MLE. The analysis proceeds through four stages: (1) data acquisition and variable specification, (2) estimation of the SUR model, (3) estimation of the SAR model, and (4) integration of both approaches into the SUR–SAR model. The stages of this research can be described through Figure 1.

### *2.1. Data Acquisition and Variable Specification*

This study employs secondary data obtained from the *Open Data Jabar* portal (`https://opendata.jabarprov.go.id/id`), managed by the West Java Provincial Government. The analysis covers 27 regencies and municipalities in West Java Province over the 2022–2024 period. The location of West Java in Indonesia, along with its 27 regencies and municipalities, can be seen in Figure 2.

The dependent variable is the Human Development Index (HDI) $(Y)$ for each regency/municipality and year, denoted as $\text{HDI}_t$ for $t = 2022,\ 2023,\ 2024$. The independent variables $(X)$ are selected according to empirical evidence and theoretical relevance in explaining regional HDI in Indonesia. These variables are:

- $\text{POV}_t$ : Poverty Rate (%) $(X_{1t})$
- $\text{NHC}_t$ : Number of Health Centers (units) $(X_{2t})$
- $\text{PDS}_t$ : Population Density (people/km²) $(X_{3t})$
- $\text{GNR}_t$ : Gini Ratio (index) $(X_{4t})$
- $\text{UNE}_t$ : Open Unemployment Rate (%) $(X_{5t})$
- $\text{CLI}_t$ : Consumption Level Index (points) $(X_{6t})$
- $\text{GPC}_t$ : Gross Regional Domestic Product (GRDP) per Capita (log) (Rupiah) $(X_{7t})$
- $\text{LMW}_t$ : Minimum Wage (log) (log Rupiah) $(X_{8t})$

The selection of economic and socio-demographic variables in this study is grounded in robust empirical evidence from the literature on human development and regional welfare disparities. Poverty and unemployment are consistently identified as major constraints on human development, as higher levels of deprivation and joblessness reduce access to education, healthcare services, and adequate living standards [5, 38]. Empirical studies across Indonesian regions confirm that poverty and unemployment exacerbate inequality and significantly weaken HDI performance [38], while regional analyses in Kalimantan and Java demonstrate a strong bidirectional relationship in which improvements in HDI significantly reduce poverty levels [43]. Income-related indicators, including gross

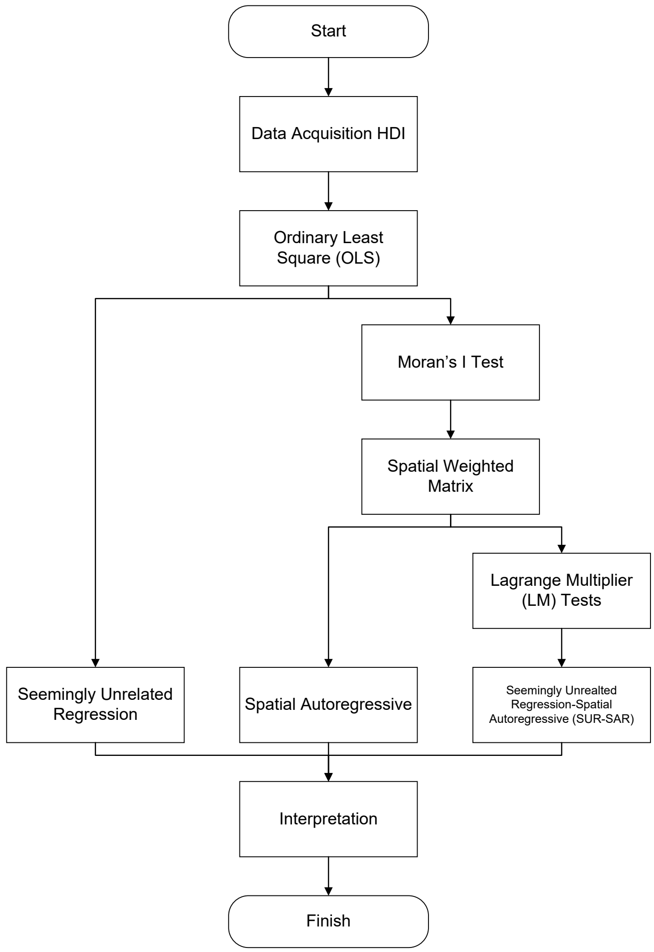


Figure 1. The Research Stages

regional domestic product (GRDP) per capita, regional income, and minimum wage, are widely employed to represent regional economic capacity and household purchasing power. Panel data analyses in Indonesia indicate that higher GRDP per capita and income levels are closely associated with improvements in HDI and reductions in regional inequality [25]. Cross-country evidence from developing economies further suggests that rising per capita income contributes to better educational attainment and health outcomes, although the magnitude of these effects may be moderated by income inequality [12].Income inequality, captured by the Gini ratio, reflects disparities in income distribution that can weaken the translation of economic growth into human development gains. Empirical evidence across Indonesian provinces shows that the Gini ratio has a significant effect on HDI and other welfare indicators [31], while studies on inequality determinants highlight the critical roles of HDI, unemployment, and poverty in shaping income distribution dynamics [37]. Population density is incorporated to account for agglomeration effects and pressure on public infrastructure and services, as commonly applied in regional welfare and poverty analyses in West Java and other regions [32]. Finally, the number of health centers is used as a proxy for health infrastructure availability, as access to healthcare facilities has been shown to be a key component of HDI improvement and poverty reduction [5, 38]. Collectively, these variables have been demonstrated to significantly explain variations in HDI across regions in Indonesia and other developing economies. The data are measured consistently across the three years to ensure comparability.

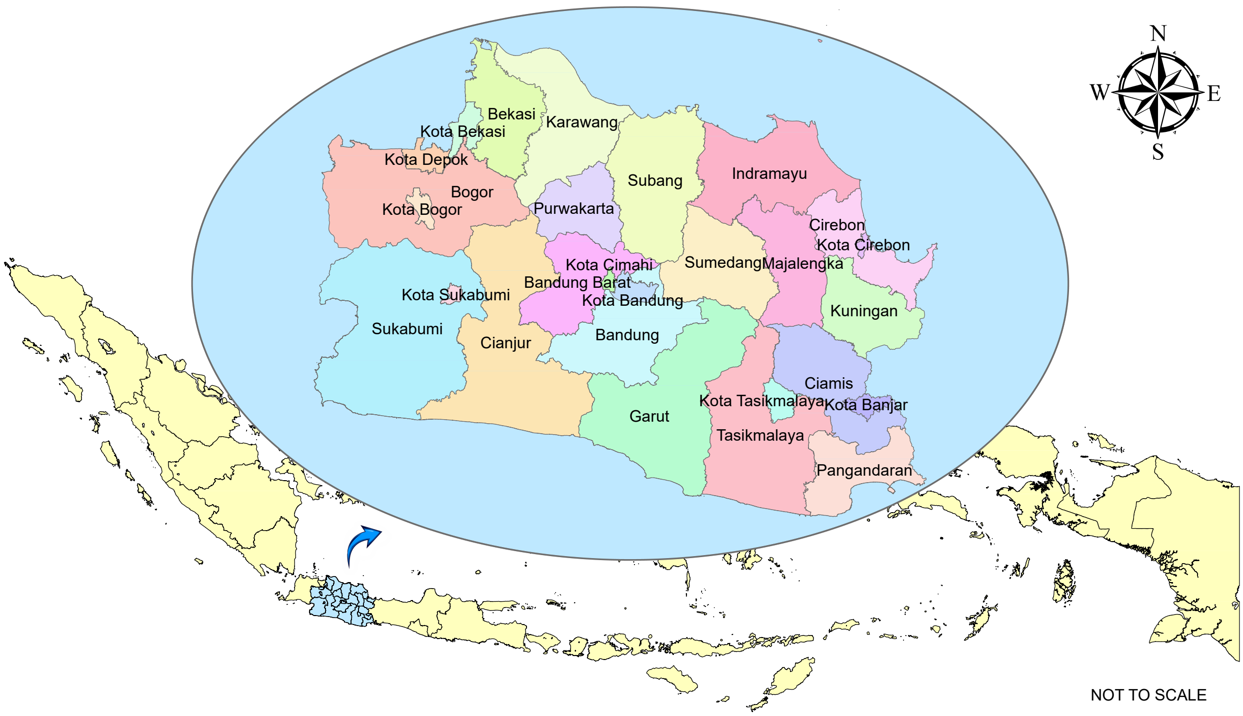


Figure 2. West Java Maps

The system of equations for the SUR–SAR model estimated by MLE is expressed as follows:

$$
\begin{aligned}
y_{22} &= \rho_1 \mathbf{W} y_{22} + \beta_{0,22} + \beta_{1,22}X_{1,22} + \beta_{2,22}X_{2,22} + \beta_{3,22}X_{3,22} + \beta_{4,22}X_{4,22} \\
&\quad + \beta_{5,22}X_{5,22} + \beta_{6,22}X_{6,22} + \beta_{7,22}X_{7,22} + \beta_{8,22}X_{8,22} + \varepsilon_{22} \qquad (1) \\
y_{23} &= \rho_2 \mathbf{W} y_{23} + \beta_{0,23} + \beta_{1,23}X_{1,23} + \beta_{2,23}X_{2,23} + \beta_{3,23}X_{3,23} + \beta_{4,23}X_{4,23} \\
&\quad + \beta_{5,23}X_{5,23} + \beta_{6,23}X_{6,23} + \beta_{7,23}X_{7,23} + \beta_{8,23}X_{8,23} + \varepsilon_{23} \qquad (2) \\
y_{24} &= \rho_3 \mathbf{W} y_{24} + \beta_{0,24} + \beta_{1,24}X_{1,24} + \beta_{2,24}X_{2,24} + \beta_{3,24}X_{3,24} + \beta_{4,24}X_{4,24} \\
&\quad + \beta_{5,24}X_{5,24} + \beta_{6,24}X_{6,24} + \beta_{7,24}X_{7,24} + \beta_{8,24}X_{8,24} + \varepsilon_{24} \qquad (3)
\end{aligned}
$$

Each equation represents the spatial autoregressive HDI model for one year (2022, 2023, 2024). The term $\rho_t \mathbf{W} y_t$ captures spatial dependence, while the error components $\varepsilon_t$ are assumed to be correlated across equations, following:

$$Var(\varepsilon) = \mathbf{\Sigma} \otimes I_{27}, \qquad (4)$$

where $\mathbf{\Sigma}$ is the cross-equation covariance matrix representing contemporaneous correlations across years, and $I_{27}$ is the identity matrix for the 27 spatial units.

### *2.2. Seemingly Unrelated Regression Model (SUR)*

The Seemingly Unrelated Regression (SUR) model, first introduced by Zellner [48], extends the classical linear regression model to a system of multiple equations that may have different dependent and independent variables. Although each equation can appear unrelated, the error terms across equations are assumed to be correlated, allowing efficiency gains through joint estimation. According to Wickens [45], in general, the SUR model for $M$ equations can be expressed as:

$$
\begin{aligned}
y_{1i} &= \beta_{11}X_{1i,1} + \beta_{12}X_{1i,2} + \cdots + \beta_{1K_1}X_{1i,K_1} + \varepsilon_{1i} \\
y_{2i} &= \beta_{21}X_{2i,1} + \beta_{22}X_{2i,2} + \cdots + \beta_{2K_2}X_{2i,K_2} + \varepsilon_{2i} \\
&\vdots \\
y_{Mi} &= \beta_{M1}X_{Mi,1} + \beta_{M2}X_{Mi,2} + \cdots + \beta_{MK_M}X_{Mi,K_M} + \varepsilon_{Mi} \\
i &= 1,\ 2,\ \ldots,\ N
\end{aligned} \tag{5}
$$

Using matrix notation, Equation (5) can be written as:

$$\mathbf{y}_m = \boldsymbol{\beta}_m \mathbf{X}_m + \varepsilon_m \tag{6}$$

where $\mathbf{y}_m$ is an $n_i \times 1$ vector of responses, $\mathbf{X}_m$ is an $n_i \times k_i$ matrix of predictors, $\boldsymbol{\beta}_i$ is a $k_i \times 1$ parameter vector, and $\varepsilon_i$ is an $n_i \times 1$ error vector.

The error term follows:

$$E\left(\varepsilon_i\right) = 0, Var\left(\varepsilon_i\right) = \mathbf{\Sigma} \otimes \mathbf{I}_n, \tag{7}$$

where $\mathbf{\Sigma}$ is the cross-equation covariance matrix and $I_n$ is the identity matrix. This indicates that while observations within an equation are independent, the residuals between equations may be correlated.

Parameter estimation in the SUR model is typically performed using MLE, which explicitly account for the covariance structure among equations to produce more efficient estimates [7, 33]. When the error terms across equations are uncorrelated (i.e., the covariance matrix $\mathbf{\Sigma}$ is diagonal), the SUR framework simplifies to a set of independent OLS regressions without efficiency loss [1]. However, if the error terms are contemporaneously correlated, SUR estimators such as MLE yield more efficient parameter estimates than OLS by leveraging cross-equation information [24, 34]. Consequently, the SUR model enhances estimation accuracy in systems where different equations share unobserved shocks or contemporaneous disturbances, making it a valuable methodological tool in economics, regional development, and social science research [18, 21].

### *2.3. Spatial Dependence*

Spatial econometric analysis is complicated not only by considerations of sample size and distributional assumptions, but also by the inherent presence of spatial dependence. This dependence is formally represented through the spatial weight matrix $\mathbf{W}$. The spatial weights matrix $\mathbf{W}$ is a central element in spatial analysis as it represents the intensity of inter-regional relationships and determines how spatial dependence is modeled in econometric approaches such as the Spatial Autoregressive (SAR), Spatial Error Model (SEM), and Spatial Durbin Model (SDM).Traditionally, $\mathbf{W}$ is constructed based on geographical proximity using contiguity methods, such as rook or queen criteria, or physical distance, where weights decline as the distance between spatial units increases. However, recent developments in the literature indicate that inter-regional interactions are not always governed by geographical proximity. This has led to the development of customized spatial weights matrices, including those based on economic distance, which link regions according to similarities in economic characteristics rather than physical location [14, 16].

Economic distance between regions $i$ and $j$ can be defined, for example, as the absolute difference in a selected economic indicator:

$$d_{ij}^{\text{econ}} = |x_i - x_j|, \tag{8}$$

or using a multivariate Euclidean distance based on $m$ economic indicators:

$$d_{ij}^{\text{econ}} = \sqrt{\sum_{k=1}^{m} (x_{ik} - x_{jk})^2}. \tag{9}$$

The resulting economic distance is then transformed into spatial weights, for instance, by taking its inverse:

$$w_{ij} = \frac{1}{d_{ij}^{\text{econ}}}. \tag{10}$$

The selection of the spatial weights matrix $\mathbf{W}$ remains inherently subjective, as there is no universally accepted criterion for determining its optimal structure. Consequently, strong theoretical justification and row-normalization are commonly applied to ensure interpretability and numerical stability in spatial econometric modeling.

Moran's I is one of the earliest and most widely used statistics for detecting spatial dependence in geographical data. Originally proposed by [27], this statistic evaluates whether the spatial distribution of a variable exhibits clustering, dispersion, or randomness, and it has become a standard diagnostic tool in exploratory spatial data analysis. Conceptually, Moran's I compares the spatial covariance between observations, as defined by the spatial weights matrix $\mathbf{W}$, with the overall variance of the variable. The value of Moran's I ranges from $-1$ to $1$, where a positive value indicates positive spatial autocorrelation (spatial clustering), a negative value indicates negative spatial autocorrelation (spatial dispersion), and a value close to zero suggests a random spatial pattern.

Formally, Moran's I statistic is calculated as:

$$I = \frac{n}{S_0} \frac{\sum_i \sum_j w_{ij} (y_i - \bar{y}) (y_j - \bar{y})}{\sum_i (y_i - \bar{y})^2}, \tag{11}$$

where $n$ denotes the number of spatial units, $y_i$ is the value of the variable at location $i$, $\bar{y}$ is the global mean, $w_{ij}$ represents the elements of the spatial weights matrix, and $S_0 = \sum_i \sum_j w_{ij}$ is the sum of all spatial weights [2].

The statistical significance of Moran's I is assessed by comparing the observed value with its expected value and variance under the null hypothesis of spatial randomness, typically assuming either randomization or normality. As a fundamental diagnostic test, the results of Moran's I provide essential justification for the application of spatial econometric models such as SAR, SEM, or SLX [39].

### *2.4. Spatial Regression Model (SAR)*

The Spatial Regression Model extends classical regression by explicitly incorporating the concept of spatial dependence, which reflects the idea that observations located near one another tend to exhibit stronger relationships than those farther apart. This principle is rooted in Tobler's First Law of Geography, which states that "everything is related to everything else, but near things are more related than distant things" [41]. Accordingly, spatial association becomes an inherent feature of regional and geographically referenced data, and ignoring this dependence may lead to biased or inefficient empirical results.

The presence of spatial dependence is commonly assessed using Moran's I statistic calculated by Equation (11), which measures the degree of spatial autocorrelation in the data. The computation of Moran's I requires the specification of a spatial weight matrix, denoted as $\mathbf{W}$. Spatial weight matrices define the structure of spatial interactions by determining which regions are considered neighbors and how strongly they are connected. Contiguity-based spatial relationships may be specified using rook, bishop, or queen criteria, where neighboring units are identified by a shared boundary, a shared vertex, or a combination of both [3]. Alternatively, the spatial structure can be defined using customized weighting schemes, such as economic distance, transportation connectivity, or social linkages [17]. Once spatial dependence is detected and an appropriate spatial weight matrix is specified, spatial regression modeling can be formally implemented.

Anselin [3] formulated the general spatial regression model as:

$$\begin{aligned} \mathbf{y} &= \rho \mathbf{W}\mathbf{y} + \mathbf{X}\beta + \mathbf{u}, \text{ where} \\ \mathbf{u} &= \lambda \mathbf{W}\mathbf{u} + \varepsilon \end{aligned} \tag{12}$$

where $\mathbf{y}$ is the dependent variable, $\mathbf{X}$ the matrix of independent variables, $\mathbf{W}$ the spatial weights matrix, $\rho$ the spatial autoregressive coefficient, $\lambda$ the spatial error coefficient, and $\varepsilon$ the error term.

Depending on the parameters, this general form yields several models:

- If $\rho = 0$ and $\lambda = 0$: Classical Linear Regression.
- If $\lambda = 0$: Spatial Autoregressive Model (SAR), captures dependence in the dependent variable.
- If $\rho = 0$: Spatial Error Model (SEM), accounts for correlated errors.
- If both $\rho$ and $\lambda$ are nonzero: Spatial Autocorrelation Model (SAC).

Spatial regression provides a powerful and robust framework for modeling interaction effects across geographic locations, allowing researchers to identify spatial clustering, diffusion processes, and spillover patterns in economic, social, and environmental data [20]. Unlike standard regression models that assume independent observations, spatial regression explicitly accounts for spatial dependence and autocorrelation among neighboring units, leading to unbiased and more efficient parameter estimates [11, 22]. By incorporating spatial lags or spatially correlated error structures, these models capture interdependencies that reflect real-world processes such as regional policy spillovers, economic diffusion, or environmental externalities, thereby enhancing empirical validity, reliability, and explanatory power in spatial data analysis [47, 49].

### 2.5. SUR–SAR Model

The first step prior to estimating the SUR–SAR model is to to assess both the presence and the nature of spatial dependence through Lagrange Multiplier (LM) diagnostics, which help identify whether spatial effects arise in the dependent variable, the error term, or both. Following Anselin [3], the LM-Lag test evaluates spatial autocorrelation in the dependent variable, whereas the LM-Error test detects correlation in the disturbance term, their robust counterparts are designed to distinguish the dominant spatial process when multiple sources of dependence are present [4]. In multi-equation systems, these diagnostics are extended as LM-SUR tests to assess spatial lag ($LM^{SUR}_{SAR}$) or spatial error ($LM^{SUR}_{SEM}$) dependence across correlated equations [29, 30]. Although conventional LM tests may be oversized, the robust forms proposed Anselin [4] are widely recommended to select the appropriate model specification whether SUR-SAR, SUR-SEM, or SUR-SARAR [8, 23, 28]. Once the relevant spatial process is confirmed, the SUR–SAR model can then be estimated.

The SUR–SAR model combines two important econometric frameworks, the SUR model, which accounts for correlated errors across multiple equations, and the SAR model, which incorporates spatial dependence among regions [3, 48]. This integration allows the simultaneous estimation of several spatial regression equations that share cross-equation correlations and spatial interactions.

For $M$ equations, the SUR–SAR system can be written as:

$$\begin{aligned} \mathbf{y}_1 &= \rho_1 \mathbf{W}\mathbf{y}_1 + \mathbf{X}_1\boldsymbol{\beta}_1 + \boldsymbol{\varepsilon}_1 \\ \mathbf{y}_2 &= \rho_2 \mathbf{W}\mathbf{y}_2 + \mathbf{X}_2\boldsymbol{\beta}_2 + \boldsymbol{\varepsilon}_2 \\ &\vdots \\ \mathbf{y}_M &= \rho_M \mathbf{W}\mathbf{y}_M + \mathbf{X}_M\boldsymbol{\beta}_M + \boldsymbol{\varepsilon}_M \end{aligned} \tag{13}$$

Using matrix notation, Equation (13) can be written as:

$$\mathbf{y}_m = \rho_m \mathbf{W}\mathbf{y}_m + \mathbf{X}_m \boldsymbol{\beta}_m + \varepsilon_m \tag{14}$$

where $\mathbf{y}_m$ is an $n_i \times 1$ vector of responses, $\boldsymbol{\rho}_m$ is an $M \times 1$ vector of spatial autoregressive coefficient, $\mathbf{X}_m$ is an $n_i \times k_i$ matrix of predictors, $\boldsymbol{\beta}_i$ is a $k_i \times 1$ parameter vector, and $\varepsilon_i$ is an $n_i \times 1$ error vector. The vector of disturbances satisfies:

$$Var\left(\varepsilon\right) = \boldsymbol{\Sigma} \otimes \mathbf{I}_n, \tag{15}$$

indicating contemporaneous correlation among the equations.

The model captures two key features, Spatial autocorrelation through the lagged dependent variable $\mathbf{W}y_i$, reflecting that outcomes in one region may depend on those in neighboring regions and Cross-equation error correlation, which improves estimation efficiency when common shocks affect all equations. Parameter estimation is typically performed using MLE. Thus, it is often preferred due to its asymptotic efficiency and consistency [3, 6].

## 3. Results and Discussion

This section presents the empirical results of the SUR–SAR modeling of the HDI for 27 regencies and municipalities in West Java Province during 2022–2024, using data on regional poverty, health facilities, population density, inequality, unemployment, consumption, gross regional domestic product, and wage. The estimation proceeded sequentially using OLS, SUR, SAR, and SUR–SAR frameworks to assess efficiency, spatial effects, and model fit.

The Ordinary Least Squares (OLS) estimation provides a baseline assessment of the determinants of the HDI in West Java across 2022–2024. The results of the OLS coefficients are presented in Table 1.

Table 1. OLS Results for HDI Determinants in West Java (2022–2024)

| Variable | 2022 | 2023 | 2024 |
|---|---|---|---|
| (Intercept) | 32.354 | 32.180 | 9.190 |
| POV $(X_1)$ | $-0.445^*$ | $-0.506^*$ | $-0.570^*$ |
| NHC $(X_2)$ | $-0.0097$ | $-0.0083$ | $-0.0131$ |
| PDS $(X_3)$ | $0.000498^*$ | $0.000552^*$ | $0.000448^*$ |
| GNR $(X_4)$ | $19.603^*$ | 14.475 | 19.509 |
| UNE $(X_5)$ | $-0.160$ | $-0.145$ | $-0.090$ |
| CLI $(X_6)$ | 0.099 | 0.146 | 0.313 |
| GPC (log) $(X_7)$ | 0.751 | 0.417 | 0.557 |
| LMW (log) $(X_8)$ | 1.369 | 1.465 | 1.844 |
| Adjusted $R^2$ | 0.893 | 0.875 | 0.886 |

According to Table 1, all OLS models demonstrate explanatory power (Adjusted $R^2$ between 0.875 and 0.893), indicating that the selected socio-economic variables collectively explain a large share of HDI variation across West Java's regions. Poverty (POV) shows a consistently negative and statistically significant effect ($p < 0.05$) in all years, suggesting that higher poverty rates are strongly associated with lower HDI outcomes. Population density (PDS) emerges as the most stable positive variables that significant ($p < 0.05$) across all years, reflecting that more urbanized areas tend to achieve higher HDI. Inequality (GNR) is positive and significant only in 2022. Meanwhile, Consumption level (CLI), GRDP per capita (GPC, log) and minimum wage (LMW, log) display positive yet statistically insignificant effects, implying that income-based indicators alone may not adequately capture differences in HDI across the region, while unemployment (UNE) has negative effects but insignificant throughout the period.

To assess potential multicollinearity, Variance Inflation Factor (VIF) diagnostics were conducted for each year's model, as presented in Table 2.

Table 2. Variance Inflation Factor (VIF) Diagnostics

| Variable | VIF 2022 | VIF 2023 | VIF 2024 |
|---|---|---|---|
| POV ($X_1$) | 2.98 | 3.60 | 3.28 |
| NHC ($X_2$) | 1.22 | 1.38 | 1.20 |
| PDS ($X_3$) | 3.85 | 4.50 | 5.38 |
| GNR ($X_4$) | 2.56 | 3.12 | 5.03 |
| UNE ($X_5$) | 2.53 | 2.03 | 1.96 |
| CLI ($X_6$) | 1.24 | 1.91 | 2.65 |
| GPC (log) ($X_7$) | 1.90 | 2.15 | 1.99 |
| LMW (log) ($X_8$) | 3.54 | 3.26 | 4.01 |

An examination of the Variance Inflation Factor (VIF) in Table 2 reveals that multicollinearity is not a severe concern for the OLS estimates in any of the years. All VIF values are well below the common threshold of 10, with the highest value being 5.38 for PDS in 2024. Specifically, Population Density (PDS) and the Minimum Wage (LMW) show moderately elevated VIFs across the period (ranging from 3.85 to 5.38 and 3.26 to 4.01, respectively), suggesting some degree of correlation with other predictors in the model. However, these values do not indicate harmful multicollinearity that would significantly bias the coefficient estimates or their standard errors. The stability and statistical significance of key variables like POV and PDS across years, despite these moderate VIFs, reinforce the robustness of their reported relationships with HDI.

The Seemingly Unrelated Regression (SUR) model jointly estimates HDI equations for 2022–2024, allowing for correlated disturbances across years. This system-based estimation improves efficiency relative to single-year OLS models and accounts for inter-year linkages in regional development patterns. The results of the SUR coefficients are presented in Table 3.

Table 3. SUR Results for HDI Determinants in West Java (2022–2024)

| Variable | 2022 | 2023 | 2024 |
|---|---|---|---|
| (Intercept) | 42.847 | 44.952 | 41.059 |
| POV ($X_1$) | $-0.375^{*}$ | $-0.385$ | $-0.412^{*}$ |
| NHC ($X_2$) | $-0.0160$ | $-0.0158$ | $-0.0169$ |
| PDS ($X_3$) | $0.000629^{*}$ | $0.000640^{*}$ | $0.000597^{*}$ |
| GNR ($X_4$) | 3.497 | 1.069 | 2.993 |
| UNE ($X_5$) | $-0.102$ | $-0.084$ | $-0.080$ |
| CLI ($X_6$) | 0.031 | 0.032 | 0.055 |
| GPC (log) ($X_7$) | 0.886 | 0.755 | 0.791 |
| LMW (log) ($X_8$) | 1.304 | 1.316 | 1.413 |
| Adjusted $R^2$ | 0.8649 | 0.8624 | 0.8686 |

The SUR results in Table 3 demonstrate consistently across all three years (Adjusted $R^2$ between 0.862 and 0.869), indicating that jointly estimating the equations improves efficiency relative to single-year OLS. Poverty (POV) remains a stable and significant negative determinant of HDI in 2022 and 2024 ($p < 0.05$), highlighting that regions with higher poverty systematically achieve lower HDI outcomes. Population density (PDS) is again the most consistently significant predictor ($p < 0.05$ for all years), confirming that more urbanized districts tend to attain higher HDI. Other socioeconomic factors, including inequality (GNR), unemployment (UNE), consumption level (CLI), GRDP per capita (GPC), and minimum wage (LMW), show positive or negative signs consistent with expectations but remain statistically insignificant, suggesting that their effects on HDI are either weak or overshadowed by structural differences across regions. The strong cross-equation residual correlations (0.98–0.99) further justify the use of SUR, indicating substantial shared shocks among HDI levels over time.

The Moran's I test is applied to examine the presence of spatial autocorrelation in the residuals of the OLS models for 2022–2024. A significant Moran's I statistic indicates that regions with similar HDI levels tend to cluster geographically, violating the assumption of independently distributed errors in OLS regression. To ensure robust detection of spatial patterns, this study compares several spatial weight matrices, including Queen Contiguity, Rook Contiguity, and Economic Distance. The results of the Moran's I test are presented in Table 4.

Table 4. Moran's I Test Results in OLS Residuals (2022–2024)

| Weight Matrix | Year | Moran's I | p-value |
|---|---|---|---|
| Queen Contiguity | 2022 | 0.0220 | 0.3317 |
| | 2023 | 0.0503 | 0.2632 |
| | 2024 | 0.0692 | 0.2189 |
| Rook Contiguity | 2022 | 0.0220 | 0.3317 |
| | 2023 | 0.0503 | 0.2632 |
| | 2024 | 0.0692 | 0.2189 |
| Economic Distance | 2022 | $0.1248^*$ | 0.0440 |
| | 2023 | $0.3806^*$ | $6.99 \times 10^{-6}$ |
| | 2024 | $0.2631^*$ | 0.0008 |

The Moran's I result in Table 4 reveals that spatial autocorrelation in OLS residuals varies across the study period and depends heavily on the choice of weight matrix. When using Queen and Rook Contiguity matrices, the Moran's I statistics are small and statistically insignificant ($p > 0.05$) for all years, suggesting that these adjacency-based matrices fail to detect the proximity and interaction between regions in West Java. However, by employing the Economic Distance weight matrix, the results consistently show positive and significant Moran's I values ($p < 0.05$) across the entire 2022–2024 period. This suggests the presence of positive spatial dependence in the residuals, whereby districts with under- or over-predicted HDI tend to cluster geographically based on economic similarities rather than mere physical borders. These findings imply that OLS is insufficient for capturing spatial interactions in 2022–2024, reinforcing the need for spatial econometric models such as SAR, SEM, or SDM to obtain unbiased and efficient estimates.

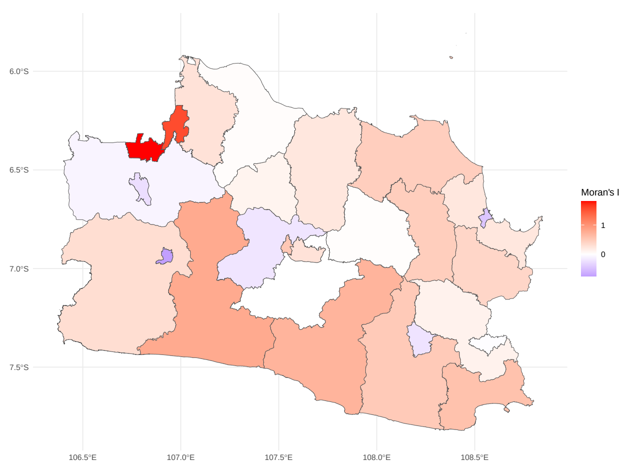


Figure 3. Local Moran's I of HDI in West Java (2024)

The Local Moran's I map (Figure 3) provides visual evidence of the spatial inequality of HDI in West Java. A significant "hotspot" of high spatial autocorrelation is observed in the Northern Coast (Pantura) region, specifically around the Jakarta-Bandung agglomeration area. In contrast, the southern and eastern parts of the province exhibit lower or insignificant spatial dependence (indicated by lighter colors), suggesting a more fragmented development pattern. This dichotomy underscores the role of spatial proximity in driving development outcomes, where the industrial centers benefit from strong positive spillovers that have yet to fully propagate to the peripheral regions.

The Spatial Autoregressive (SAR) model extends the OLS framework by incorporating a spatial lag parameter ($\rho$) to capture interregional dependence in HDI outcomes. The model was estimated for each year (2022–2024) using MLE with an inverse-distance spatial weight matrix. The results of the SAR coefficients are presented in Table 5.

Table 5. SAR Results for HDI Determinants in West Java (2022–2024)

| Variable | 2022 | 2023 | 2024 |
|---|---|---|---|
| (Intercept) | $33.597^*$ | $36.915^*$ | $28.931$ |
| POV ($X_1$) | $-0.394^*$ | $-0.440^*$ | $-0.456^*$ |
| NHC ($X_2$) | $-0.00145$ | $-0.00058$ | $-0.00516$ |
| PDS ($X_3$) | $0.000389^*$ | $0.000389^*$ | $0.000418^*$ |
| GNR ($X_4$) | $19.153^*$ | $19.279^*$ | $13.762$ |
| UNE ($X_5$) | $-0.130$ | $-0.124$ | $-0.131$ |
| CLI ($X_6$) | $0.037$ | $0.034$ | $0.119$ |
| GPC (log) ($X_7$) | $0.645$ | $0.224$ | $0.640$ |
| LMW (log) ($X_8$) | $-0.995$ | $-1.331$ | $-0.876$ |
| $\rho$ | $0.551^*$ | $0.642^*$ | $0.527^*$ |

The SAR results in Table 5 indicate persistent spatial dependence in HDI across West Java, reflected by the significant spatial autoregressive parameter $\rho$ in all years ($p < 0.05$). This confirms HDI spillover effects, where increases in HDI in one district are associated with increases in neighboring districts. Poverty (POV) remains consistently negative and significant ($p < 0.05$), showing that poverty reduction directly enhances local and neighboring HDI levels. Population density (PDS) also shows a stable and strongly positive influence ($p < 0.05$), indicating that more urbanized regions tend to have higher HDI. Inequality (GNR) is significant in 2022 and 2023 but not in 2024, suggesting its effect is less stable over time. Other variable unemployment, health centers, consumption level, GRDP per capita, and minimum wage, remain statistically insignificant, implying that socioeconomic spillovers are not driven by these factors.

Before estimating the SUR–SAR model, Lagrange Multiplier (LM) tests were performed to determine whether spatial effects are present in the system of HDI equations. The tests include $LM_{SAR}^{SUR}$ (for spatial lag dependence) and $LM_{SEM}^{SUR}$ (for spatial error dependence), along with their robust counterparts ($LM{*}_{SAR}^{SUR}$ and $LM{*}_{SEM}^{SUR}$). These diagnostics, proposed by Anselin [3] and extended by Lacambra [30], identify whether spatial interaction should be incorporated into the SUR framework. A significant $LM_{SAR}^{SUR}$ statistic indicates that the SUR–SAR model is the appropriate specification. The result of LM test is presented in Table 6.

Table 6. Lagrange Multiplier (LM) Tests for Spatial Dependence in the SUR System

| Test Statistic | Hypothesis | p-value |
|---|---|---|
| $\mathbf{LM_{SAR}^{SUR}}$ | $(H_0 : \rho = 0)$ | $0.0148^*$ |
| $\mathbf{LM_{SEM}^{SUR}}$ | $(H_0 : \lambda = 0)$ | $0.2204$ |
| $\mathbf{LM^*{}_{SAR}^{SUR}}$ | $(H_0 : \rho = 0)$ (robust) | $0.0915$ |
| $\mathbf{LM^*{}_{SEM}^{SUR}}$ | $(H_0 : \lambda = 0)$ (robust) | $0.9469$ |

According to Table 6, the LM test results indicate that the $LM^{SUR}_{SAR}$ is statistically significant ($p < 0.05$), while the $LM^{SUR}_{SEM}$ statistics are not. This finding implies that spatial dependence arises primarily from the spatially laged dependent variable, not from spatial correlation in the residuals. Therefore, the SUR–SAR model is identified as the most appropriate specification for the HDI system.

The SUR–SAR model, estimated through MLE, combines spatial lag dependence with cross-equation correlation to improve efficiency in modeling HDI across multiple years. The spatial lag parameters ($\rho$) capture interregional effects, while the contemporaneous covariance structure captures correlations among the HDI equations for 2022, 2023, and 2024. This specification addresses both spatial and temporal dependencies simultaneously. The results of the SUR-SAR coefficients are presented in Table 7.

Table 7. SUR-SAR Results for HDI Determinants in West Java (2022–2024)

| Variable | 2022 | 2023 | 2024 |
|---|---|---|---|
| (Intercept) | 13.485 | 13.668 | 14.543 |
| POV | $-0.023$ | $-0.057$ | $-0.051$ |
| NHC | $-0.009$ | $-0.006$ | $-0.007$ |
| PDS | $0.000654^*$ | $0.000616^*$ | $0.000609^*$ |
| GNR | $-2.525^*$ | $0.952$ | $0.473$ |
| UNE | $0.017$ | $0.017$ | $0.033$ |
| CLI | $0.0004$ | $0.019^*$ | $0.0099$ |
| GPC (log) | $0.980$ | $0.795$ | $0.843$ |
| LMW (log) | $1.657^*$ | $1.544^*$ | $1.606^*$ |
| $\rho$ | $0.325^*$ | $0.339^*$ | $0.324^*$ |
| $R^2$ (Equation) | 0.891 | 0.9066 | 0.9059 |

Table 8. System Diagnostics for the SUR–SAR Model

| Diagnostic Test | Statistic |
|---|---|
| Pooled $R^2$ | 0.9024 |
| Breusch–Pagan Test | $80.19^*$ (p = $2.25 \times 10^{-17}$) |
| LMM Test (Spatial Dependence) | 3.339 (p = 0.339) |
| Residual Correlations ($\rho_{12},\ \rho_{13},\ \rho_{23}$) | 0.998 / 0.996 / 0.999 |

Table 7 shows that across all years, population density (PDS) consistently emerges as the positive and significant variable ($p < 0.05$), highlighting the advantage of urbanized areas in achieving higher HDI. Consumption level (CLI) becomes significant in 2023, while inequality (GNR) is significant only in 2022. Minimum wage (LMW) is positive and statistically significant across all years ($p < 0.05$), suggesting that higher regional wage standards support improvements in HDI. The spatial lag coefficients ($\rho \approx$ 0.32–0.34) are positive and significant, indicating spatial spillover effects where HDI improvements in one district positively influence neighboring districts. These results confirm that the SUR–SAR model provides an efficient and theoretically consistent representation of HDI dynamics in West Java.

According to Table 8, the SUR–SAR model achieves pooled $R^2$ of 0.9024, indicating excellent explanatory and confirming that the combined spatial–temporal specification effectively accounts for HDI variation across all 27 regencies and cities in West Java. The Breusch–Pagan test is highly significant ($p < 0.05$), demonstrating inter-equation error correlations and validating the use of the SUR framework rather than separate OLS or SAR models. The LMM test shows no additional spatial dependence remaining in the residuals (p = 0.339), confirming that the spatial lag component successfully captures spatial interaction effects. Additionally, the variance–covariance and correlation matrices of the residuals show high correlations between equations (above 0.99), confirming that HDI across years is influenced by persistent, province-wide structural factors rather than localized shocks.

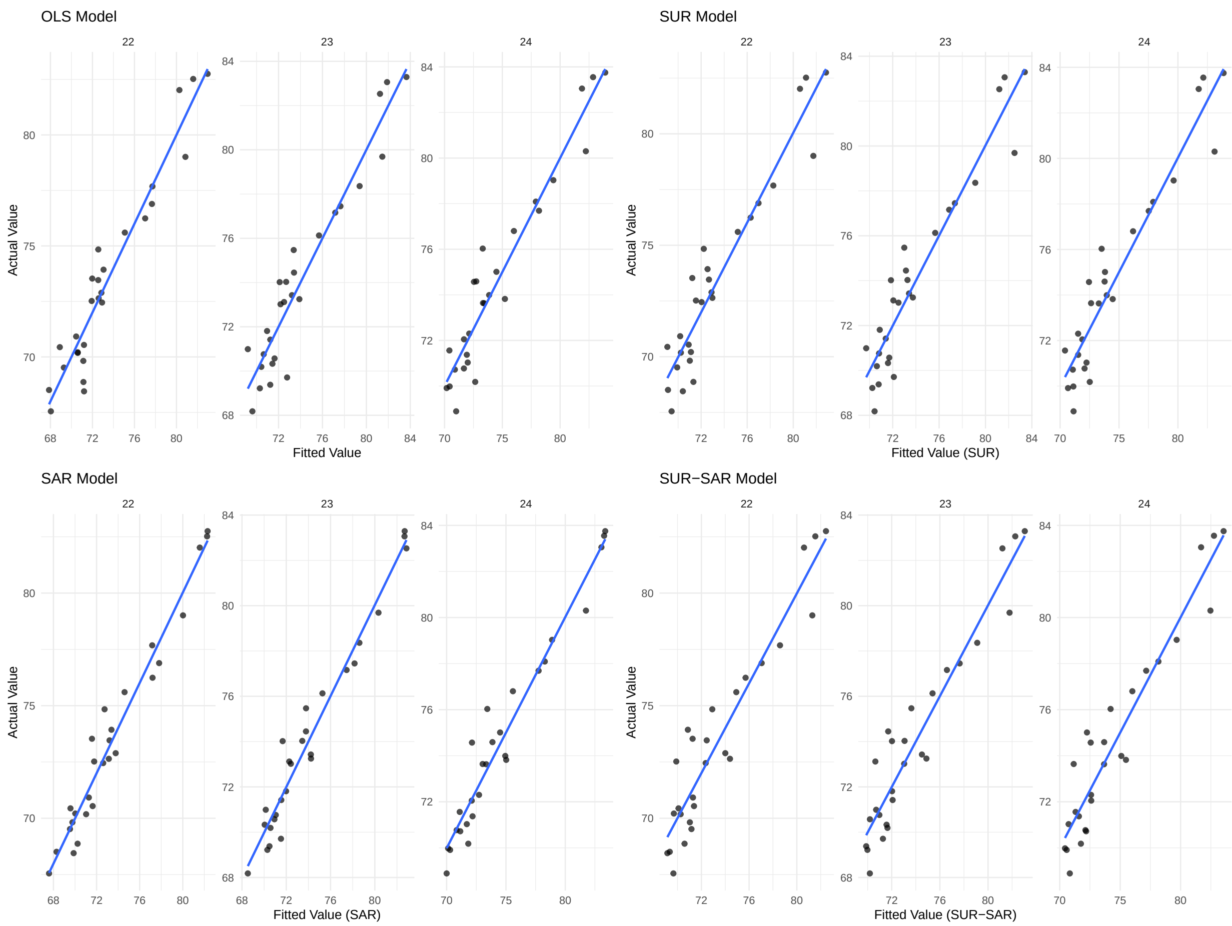


Figure 4. Fitted vs Actual HDI (2022–2024)

The fitted-value plot (Figure 4) shows that the predicted HDI values from the SUR–SAR model aligns closely with the actual observations across all 27 regencies and municipalities for 2022–2024. The fitted lines follow the observed HDI pattern with minimal deviation, confirming the model's excellent in-sample predictive performance. Regions with higher observed HDI scores also exhibit higher fitted values, suggesting that the model accurately captures inter-regional variation in HDI. This alignment demonstrates that the SUR–SAR specification effectively represents both the temporal and spatial structure of HDI dynamics in West Java.

Table 9 provides a comparative overview of significant variables across OLS, SUR, SAR, and SUR–SAR models for the 2022–2024 period, revealing several consistent patterns in the determinants of HDI in West Java. Across all model families, population density (PDS) emerges as the most stable and highly significant predictor ($p < 0.05$), reinforcing the notion that more urbanized districts benefit from better access to education, healthcare, and economic opportunities, which translate into higher HDI outcomes. Poverty (POV) shows a persistent negative effect in OLS, SUR, and especially in the SAR models, where the coefficients become significant ($p < 0.05$), highlighting the strong and direct influence of poverty reduction on HDI.

The role of income-related factors, particularly minimum wage (LMW) and GRDP per capita (GPC) varies across models. While both appear statistically insignificant in OLS and SUR, LMW becomes consistently significant in the SUR–SAR model, that once spatial dependence and inter-equation correlations are accounted, wage standards are revealed as an important structural determinant of HDI. This indicates the presence of spatial spillover effects, increases in wage levels in one district may indirectly stimulate improvements in bordering areas.

Table 9. Summary of Significant Variables and Model Fit Statistics (2022–2024)

| Variable | OLS | | | SUR | | | SAR | | | SUR-SAR | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 2022 | 2023 | 2024 | 2022 | 2023 | 2024 | 2022 | 2023 | 2024 | 2022 | 2023 | 2024 |
| POV | * | * | * | * | | * | * | * | * | | | |
| NHC | | | | | | | | | | | | |
| PDS | * | * | * | * | * | * | * | * | * | * | * | * |
| GNR | * | | | | | | * | * | | * | | |
| UNE | | | | | | | | | | | | |
| CLI | | | | | | | | | | | * | |
| GPC (log) | | | | | | | | | | | | |
| LMW (log) | | | | | | | | | | * | * | * |
| $\rho$ | | | | | | | * | * | * | * | * | * |
| AIC | 105.2 | 108.9 | 106.1 | | 107.2 | | 94.1 | 94.5 | 99.0 | | 31.9 | |
| BIC | 118.2 | 121.9 | 119.1 | | 186.2 | | 108.3 | 108.7 | 113.2 | | -0.5 | |
| Total AIC | | 320.2 | | | 107.2 | | | 287.5 | | | 31.9 | |
| Total BIC | | 359.1 | | | 186.2 | | | 330.3 | | | -0.5 | |

In contrast, GNR (inequality) exhibits mixed effects, positive in OLS and SAR but negative in SUR–SAR for 2022, reflecting differences in how each model treats error structures and spatial interactions. The sign reversal of the Gini Ratio (GNR) coefficient from positive in simpler models to negative in the SUR–SAR specification highlights the risk of omitted variable bias in non-spatial estimations. The positive association in OLS likely reflects a spurious correlation where high-growth urban centers exhibit both high inequality and high HDI. However, once spatial autocorrelation and cross-equation error structures are controlled for in the SUR–SAR model, the coefficient corrects to a negative sign, consistent with the theoretical expectation that excessive inequality hampers inclusive human development. This is in line with research conducted by Wibowo [44].

The SAR and SUR–SAR models also highlight the significance of the spatial lag parameter ($\rho$), which is positive and highly significant across all years. Furthermore, the superior performance of SAR over the standard SUR model suggests that spatial dependence is a more dominant feature of the data than cross-equation error correlation alone. While SUR improves efficiency by accounting for contemporaneous correlations between years, it fails to capture the direct spatial spillovers evident in the significant $\rho$ parameter. The SUR–SAR model bridges this gap by addressing both, resulting in the most robust estimates.

Collectively, Table 9 demonstrates that while classic models (OLS, SUR) identify PDS and POV as the dominant drivers of HDI, the inclusion of spatial dependence in SAR and SUR–SAR models uncover deeper structural influences, particularly those related to wage policy and spatial interactions. Furthermore, the model selection criteria provide strong empirical support for the SUR–SAR specification. As shown in the bottom rows of Table 9, the SUR–SAR model achieves the lowest Total AIC (31.9) and BIC ($-0.5$) compared to the OLS, SUR, and SAR models, which exhibit significantly higher values. This substantial reduction in information criteria indicates that the SUR–SAR model offers the most efficient balance between goodness-of-fit and model complexity. The SUR–SAR specification therefore provides the most comprehensive representation of HDI dynamics, integrating both spatial spillovers and cross-equation correlations to yield more robust and policy-relevant insights.

From a policy perspective, the significance of the Minimum Wage (LMW) specifically in the SUR–SAR model implies that wage policies generate spillover effects beyond administrative boundaries. This suggests that local governments should move away from isolated wage setting towards a coordinated regional approach. Harmonizing minimum wage adjustments across adjacent districts could amplify positive spatial spillovers, thereby accelerating HDI improvements collectively rather than competitively. Additionally, since poverty (POV) remains a critical factor, fiscal policies must prioritize poverty alleviation programs that are spatially targeted to under-developed clusters.

## 4. Conclusion

This study successfully addresses its three research objectives. First, it specifies and estimates a SUR–SAR model for the HDI across 27 regencies and municipalities in West Java for the 2022–2024 period, incorporating eight key socio-economic variables such as poverty, health facility availability, population density, inequality, unemployment, consumption levels, GRDP per capita, and regional minimum wage. Second, the application of MLE ensures statistical efficiency and methodological rigor, fully aligned with established spatial econometric standards. Third, the comparative assessment of OLS, SUR, SAR, and SUR–SAR models demonstrates that the SUR–SAR framework provides the most comprehensive specification, effectively capturing both spatial dependence and inter-year correlations.

The empirical findings reveal that population density (PDS) consistently emerges as the most influential and statistically robust determinant, while poverty (POV) exhibits stable negative effects across multiple models. The regional minimum wage (LMW) becomes significant only after accounting for spatial interactions and inter-equation correlations in the SUR–SAR framework, indicating its strategic role in broader regional development dynamics. Meanwhile, inequality, health centers, unemployment, consumption levels, and GRDP per capita show varying effects depending on model specification. The significant spatial lag parameter confirms meaningful HDI spillover effects across neighboring districts. Crucially, model diagnostics confirm that the SUR–SAR specification utilizing the Economic Distance weight matrix is the superior model, achieving the lowest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values. This statistical evidence underscores that capturing spatial dependence through economic proximity, rather than simple geographic contiguity, yields the most precise and information-efficient representation of HDI dynamics in West Java.

Despite these contributions, the study remains subject to several limitations. Its temporal scope is restricted to three years and one province, limiting broader generalization. To overcome these constraints and advance regional development analysis, future research is encouraged to integrate modern computational approaches. Specifically, the application of Machine Learning algorithms, such as Gradient Boosting or Spatial Random Forests, could uncover complex non-linear relationships and heterogeneous spatial effects often missed by parametric linear models. Furthermore, employing Bayesian Spatial econometrics would provide a more flexible inference framework, allowing for the incorporation of prior knowledge and better handling of parameter uncertainty in limited-sample regional contexts compared to standard Maximum Likelihood Estimation.

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