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Analysis of Indonesia's Gross Regional Domestic Product using a Spatially Filtered Unconditional Quantile Regression Approach

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ABSTRACT

Analyzing Indonesia's Gross Regional Domestic Product (GRDP) is crucial for understanding regional economic disparities characterized by heterogeneity and spatial dependence. However, previous studies using mean regression or standard Unconditional Quantile Regression (UQR) often ignore spatial dependence, potentially biasing distributional estimates. Substantively, this study aims to examine how socioeconomic factors influence regional economic performance across different levels of GRDP in Indonesia. To address the methodological gap, this study applies Spatially Filtered Unconditional Quantile Regression (SF-UQR), which captures heterogeneous effects across the GRDP distribution while accounting for spatial dependence. Using cross-sectional data of Indonesian districts and cities from Statistics Indonesia (BPS) in 2023, GRDP is specified as the response variable, with five explanatory variables: human development index, minimum wage, number of workers, original local government revenue, and poverty rate. The analysis compares UQR and SF-UQR across selected quantiles. The results reveal substantial heterogeneity. Human development index and original local government revenue consistently show positive effects, poverty rate negatively affects lower quantiles, minimum wage exhibits a shifting pattern, and number of workers is significant mainly at middle and upper quantiles. SF-UQR outperforms standard UQR, achieving an adjusted R^2 of 0,67 compared to 0,52 under UQR. Methodologically, this study highlights the relevance of incorporating spatial filtering into UQR when analyzing regional economic data characterized by spatial dependence, providing an alternative distributional perspective on regional economic dynamics. From a policy perspective, the findings indicate that development strategies should consider both distributional heterogeneity and spatial dependence. Overall, the results highlight the necessity of spatially informed and distribution-sensitive policy design to reduce regional economic disparities in Indonesia.

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A. INTRODUCTION

Gross Regional Domestic Product (GRDP) reflects the economic performance of a region (Pravitasari et al., 2021). It measures the total value added generated within a region over a given period (*Badan Pusat Statistika*, 2025). At the district/city level, GRDP reflects differences in local economic capacity and structural development because it captures the economic output produced within a specific administrative area. Consequently, GRDP is often used to evaluate regional development patterns and to compare economic performance across regions. However, the distribution of GRDP across regions often exhibits considerable disparities, resulting in uneven regional development (Fitri & Rindiani, 2024), thereby making GRDP an important reference for understanding disparities in regional economic capacity and identifying areas that require policy attention.

The distribution of GRDP across districts/cities in Indonesia remained highly uneven in 2023. Nationally, Java accounted for 57,05 percent of Indonesia's Gross Domestic Product (GDP) (PwC Indonesia, 2024), while other regions contributed substantially smaller shares, including Sumatra (22,01 percent), Kalimantan (8,49 percent), Sulawesi (7,10 percent), Bali and Nusa Tenggara (2,77 percent), and Maluku–Papua (2,58 percent). Although positive growth was observed across all regions, the distribution of economic output remains markedly unequal, indicating persistent disparities in regional economic capacity (Amalia & Fitrijanto, 2022). These disparities can be driven by complex interactions among geographical, social, economic, and political factors at the regional level (Yuliana et al., 2024).

Empirical analyses of GRDP determinants in Indonesia have predominantly relied on classical mean-based regression models, as employed in studies such as Istiqomah et al. (2019); Yuliadi (2020). While such approaches are useful for estimating average relationships, they may provide an incomplete representation when economic outcomes are unevenly distributed. Classical regression assumes normality and homoskedasticity, and violations of these assumptions can worsen estimation results (Rajh-Weber et al., 2025). More importantly, focus on the mean may limit research questions and conclusions (Hird et al., 2024). As a result, models that rely solely on average effects may overlook important variations that occur across different segments of the GRDP distribution.

Substantial disparities in GRDP across regions suggest that socioeconomic determinants may exert different influences at different levels of regional economic performance. To capture such heterogeneous effect, quantile-based regression provides a framework that allows explanatory variables effects to vary across points of the response distribution (Wang et al., 2024). In addition, economic data such as GRDP are inherently linked to geographic location and frequently exhibit spatial patterns (Otieno, 2024; Shang et al., 2025; Yin et al., 2024), further emphasizing the need for analytical approaches that account not only for distributional heterogeneity but also for spatial effects.

Unconditional Quantile Regression (UQR) evaluates the relationship between explanatory variables and the marginal distribution of the response variable using the recentered influence function (Gregory & Zierahn, 2022; Jiang & Yu, 2024). UQR examines how variations in explanatory variables are associated with changes in the overall distribution of the outcome variable. This approach allows researchers to analyze distributional patterns across different points of the response distribution and assess how policy or socioeconomic factors relate to the entire distribution rather than only the mean (Alejo et al., 2025; Liou, 2019), as demonstrated in Agyire-Tettey et al. (2018).

Recent developments further extend UQR by incorporating spatial filtering techniques to account for spatial dependence as proposed in Murakami & Seya (2019). Spatial filtering improves model specification and estimation stability by extracting latent spatial structures embedded in the data (McCord et al., 2022; McCord et al., 2019; Zhang et al., 2018). Several empirical studies applying SF-UQR—such as Sakizadeh & Martín (2021); Sakizadeh & Milewski

(2023); Vogt & Fochezatto (2023); Adjei et al. (2026) highlight its advantages in modeling distributional and spatial effects.

Despite the growing development of quantile-based and spatial econometric approaches, a critical gap remains in the empirical analysis of Indonesian GRDP. To the best of our knowledge, no study has jointly examined distributional heterogeneity and spatial dependence in Indonesian GRDP using the SF-UQR framework. This study aims to examine how socioeconomic determinants influence GRDP across different quantiles of its marginal distribution by applying the established SF-UQR framework to Indonesian regional economic data. In doing so, it provides the first empirical evidence on the joint role of distributional heterogeneity and spatial dependence in Indonesian GRDP and offers distribution-sensitive insights to inform evidence-based regional development policy discussions.

B. METHODS

The analysis is conducted using cross-sectional GRDP data for the year 2023, covering 514 districts and cities throughout Indonesia. The dataset was obtained from Statistics Indonesia. Both the response variable and all explanatory variables are expressed in numerical form. The response and explanatory variables employed in this research are as shown in Table 1.

Table 1. Variables Employed in the Analysis

Variables	Description	Unit
Y	GRDP based on constant prices	Billion Rupiah
X_1	Human development index	Percent
X_2	Minimum wage	Million Rupiah
X_3	Number of workers	Person
X_4	Original local government revenue	Billion Rupiah
X_5	Poverty rate	Percent

Data analysis was conducted in RStudio according to the following stages:

1. Conducting an exploratory analysis of Indonesia's 2023 GRDP data. This step includes examining skewness and kurtosis, generating thematic maps to observe the distribution patterns of GRDP and examining correlations among variables.
2. Assessing multicollinearity between explanatory variables through the Variance Inflation Factor (VIF). According to Kim (2019), the VIF is calculated as follows:

$$VIF = \frac{1}{(1 - R^2)} \tag{1}$$

   where R^2 denotes the coefficient of determination.
3. Specifying the spatial weight matrix to be used. A distance-based spatial weight matrix is constructed to accommodate Indonesia's archipelagic structure, where contiguity-based matrices may generate disconnected components. Several distance thresholds are evaluated, and the optimal specification is selected based on the highest Global Moran's I value for GRDP, indicating the strongest spatial autocorrelation. The resulting matrix is row-standardized prior to further analysis.

4. Conducting a test for spatial dependence through Moran's I. Moran's I is as follows:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{\bar{x}})(x_j - \bar{\bar{x}})}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \sum_{i=1}^{n}(x_i - \bar{\bar{x}})^2} \tag{2}$$

where x_i denotes the observed value at location i, x_j denotes the observed value at location j, $\bar{x}$ represents the average observed value across all locations and w_{ij} denotes the element of the spatial weight matrix corresponding to location i and j.

5. Conducting a spatial heterogeneity test using the Breusch-Pagan (BP) test. The formula for BP test statistic is as follows (Kholifia et al., 2021):

$$BP = \left(\frac{1}{2}\right) \boldsymbol{f}'\boldsymbol{X}(\boldsymbol{X}'\boldsymbol{X})^{-1}\boldsymbol{X}'\boldsymbol{f} \tag{3}$$

where

$$f_i = \left(\frac{\hat{\varepsilon}_i^2}{\hat{\sigma}^2} - 1\right) \tag{4}$$

$\hat{\varepsilon}_i^2$ denotes the squared residual at location i obtained from the ordinary least square regression parameter estimates, $\hat{\sigma}^2 = \sum_{i=1}^{n} \hat{\varepsilon}_i^2$ and $\boldsymbol{X}$ is $n \times (p+1)$ matrix of explanatory variables.

6. Conducting data analysis using the SF-UQR method:
   a. Estimating the parameters of the SF-UQR model.
      The SF-UQR model is specified as follows:

$$\boldsymbol{r}_\tau = \boldsymbol{X\beta}_\tau + \boldsymbol{E\gamma}_\tau + \boldsymbol{\varepsilon}_\tau \text{ with } \boldsymbol{\gamma}_\tau \sim N\left(\boldsymbol{0}_L, \sigma_{\gamma,\tau}^2 \boldsymbol{\Lambda}(\alpha_\tau)\right) \text{ and } \boldsymbol{\varepsilon}_\tau \sim \boldsymbol{N}(\boldsymbol{0}, \sigma_\tau^2 \boldsymbol{I}) \tag{5}$$

where, $\boldsymbol{r}_\tau$ denotes the $n \times 1$ vector whose i-th element is the recentered influence function RIF$(y_i; \hat{q}_\tau)$, $\boldsymbol{X}$ denotes the matrix of explanatory variables, $\boldsymbol{\beta}_\tau$ denotes the vector of regression coefficients at quantiles τ, $\boldsymbol{E}$ is the spatial eigenvector matrix of dimension $n \times L$, $\boldsymbol{\gamma}_\tau$ is vector with size $L \times 1$ of spatial random effects at quantile τ and $\boldsymbol{\varepsilon}_\tau$ is an $n \times 1$ vector of random errors. The vector $\boldsymbol{0}_L$ denotes an $L \times 1$ zero vector, $\sigma_{\gamma,\tau}^2$ denotes the variance parameter governing the spatial random effects, which quantifies the strength of spatial dependence at quantile τ, $\boldsymbol{\Lambda}(\alpha_\tau) = \left(\frac{\sum_l \lambda_l}{\sum_l \lambda_l^{\alpha_\tau}}\right) \boldsymbol{\Lambda}^{\alpha_\tau}$, α_τ represents the level of spatial dependence at quantile τ, σ_τ^2 denotes the error variance at quantile τ and $\boldsymbol{I}$ denotes the $n \times n$ identity matrix. The response variable $\boldsymbol{Y}$ is first transformed into the RIF, defined as:

$$\begin{aligned} RIF(y_i, q_\tau) &= q_\tau + IF(y_i, q_\tau) \\ &= q_\tau + \frac{\tau - \mathrm{I}\{y_i > q_\tau\}}{f(q_\tau)} \end{aligned} \tag{6}$$

where q_τ denotes the τ-th quantile and $IF(y_i, q_\tau)$ is the influence function. The RIF represents the unconditional (marginal) quantile of the response variable. Subsequently, the RIF is regressed on the explanatory variables $\boldsymbol{X}$ to estimate the parameter vector $\boldsymbol{\beta}_\tau$. The equation (5) can be equivalently expressed as:

$$\boldsymbol{r}_\tau = \boldsymbol{X}\boldsymbol{\beta}_\tau + \boldsymbol{E}\boldsymbol{V}(\boldsymbol{\theta}_\tau)\boldsymbol{u}_\tau + \boldsymbol{\varepsilon}_\tau \text{ with } \boldsymbol{u}_\tau \sim N(\boldsymbol{0}_L, \sigma_\tau^2 \boldsymbol{I}_L) \text{ and } \boldsymbol{\varepsilon} \sim \boldsymbol{N}(\boldsymbol{0}, \sigma_\tau^2 \boldsymbol{I}) \tag{7}$$

where $\boldsymbol{I}_L$ denotes an $L \times L$ identity, $\boldsymbol{\theta}_\tau \in \left\{\sigma_{\gamma,\tau}^2,\ \alpha_\tau\right\}$ and $\boldsymbol{V}(\boldsymbol{\theta}_\tau) = \left(\frac{\sigma_{\gamma,\tau}}{\sigma_\tau}\right)\boldsymbol{\Lambda}^{\frac{1}{2}}(\alpha_\tau)$. The estimation of parameter vector $\widehat{\boldsymbol{\beta}}_\tau$ is carried out using the restricted maximum likelihood (REML) approach. The REML log-likelihood function is given by:

$$\begin{aligned} l(\boldsymbol{\theta}_\tau) = -\frac{1}{2} log \left|\begin{bmatrix} \boldsymbol{X}'\boldsymbol{X} & \boldsymbol{X}'\boldsymbol{E}\boldsymbol{V}(\boldsymbol{\theta}_\tau) \\ \boldsymbol{V}(\boldsymbol{\theta}_\tau)\boldsymbol{E}'\boldsymbol{X} & \boldsymbol{V}(\boldsymbol{\theta}_\tau)^2 + \boldsymbol{I}_L \end{bmatrix}\right| \\ -\frac{N-K}{2}\left(1 + log\left(\frac{2\pi d(\boldsymbol{\theta}_\tau)}{N-K}\right)\right) \end{aligned} \tag{8}$$

where

$$d(\boldsymbol{\theta}_\tau) = \left\|\boldsymbol{r}_\tau - \boldsymbol{X}\widehat{\boldsymbol{\beta}}_\tau - \boldsymbol{E}\boldsymbol{V}(\boldsymbol{\theta}_\tau)\widehat{\boldsymbol{u}}_\tau\right\|^2 + \|\widehat{\boldsymbol{u}}_\tau\|^2 \tag{9}$$

The estimators of $\boldsymbol{\beta}_\tau$ and $\boldsymbol{u}_\tau$ are obtained as:

$$\begin{bmatrix} \widehat{\boldsymbol{\beta}}_\tau \\ \widehat{\boldsymbol{u}}_\tau \end{bmatrix} = \begin{bmatrix} \boldsymbol{X}'\boldsymbol{X} & \boldsymbol{X}'\boldsymbol{E}\boldsymbol{V}(\boldsymbol{\theta}_\tau) \\ \boldsymbol{V}(\boldsymbol{\theta}_\tau)\boldsymbol{E}'\boldsymbol{X} & \boldsymbol{V}(\boldsymbol{\theta}_\tau)^2 + \boldsymbol{I}_L \end{bmatrix}^{-1} \begin{bmatrix} \boldsymbol{X}'\boldsymbol{r}_\tau \\ \boldsymbol{V}(\boldsymbol{\theta}_\tau)\boldsymbol{E}'\boldsymbol{r}_\tau \end{bmatrix} \tag{10}$$

Parameter estimation using REML is performed through the following stages (Murakami & Seya, 2019):
1) $\boldsymbol{\theta}_\tau$ is obtained by maximizing equation (8) using the plug-in expressions derived from equation (9) and (10)
2) The parameters $\boldsymbol{\beta}_\tau$ and $\boldsymbol{\gamma}_\tau = \boldsymbol{V}(\boldsymbol{\theta}_\tau)\boldsymbol{u}_\tau$ are then estimated by inserting the estimated $\boldsymbol{\theta}_\tau$ into equation (10)
3) The variance component σ_τ^2 is subsequently estimated as describe below:

$$\hat{\sigma}_\tau^2 = \frac{\left\|\boldsymbol{r}_\tau - \boldsymbol{X}\widehat{\boldsymbol{\beta}}_\tau - \boldsymbol{E}\boldsymbol{V}(\boldsymbol{\theta}_\tau)\widehat{\boldsymbol{u}}_\tau\right\|^2}{N-K} \tag{11}$$

b. Identifying explanatory variables that significantly influence the response variable at quantile 0,1, 0,25, 0,5, 0,75 and 0,9.

7. Model evaluation.

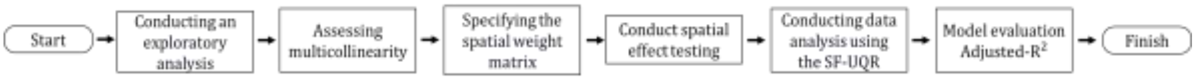


Figure 1. Methodological Flowchart

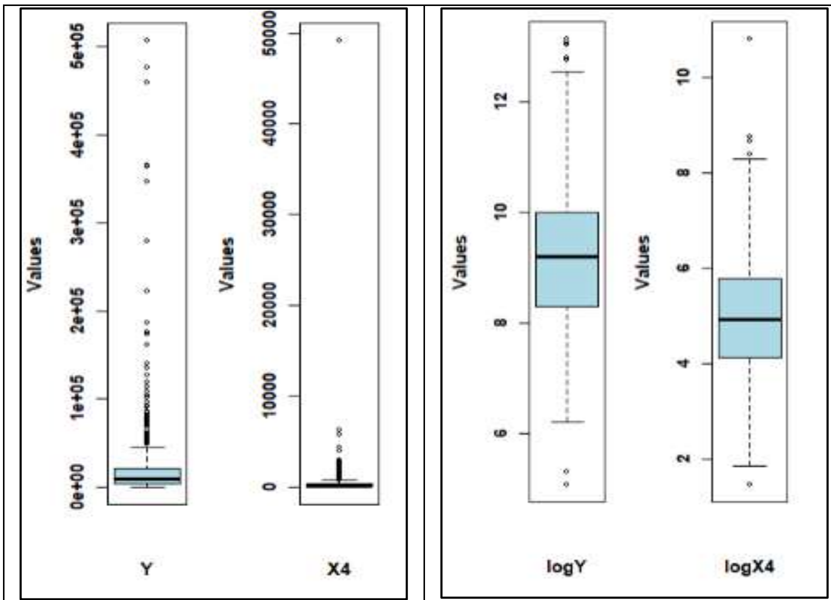
C. RESULT AND DISCUSSION

1. Data Exploration

Economic data often exhibit pronounced skewness and kurtosis, as evident from Table 2 and Figure 2—particularly for the response variable Y and the explanatory variable X_4. Taking the logarithm of GDP and other economic indicators improves model fit and yields more robust inference compared to using raw variables, especially when the data display skewness. Examples of such economic data include GDP, income, and prices (Chellai, 2025). Accordingly, this study applies a logarithmic transformation to the response variable Y and the explanatory variable X_4. Following the logarithmic transformation, Table 2 shows that the skewness and kurtosis of the response variable decreased from 5,80 and 40,27 to 0,23 and 0,27, respectively. Similarly, for the explanatory variable, skewness and kurtosis declined from 8,90 and 78,30 to 0,84 and 2,65, respectively. Figure 2 presents boxplots of both the response and explanatory variables.

Table 2. Skewness and Kurtosis of the Response and Explanatory Variables

Variables	**Y**	**logY**	$\mathbf{X_1}$	$\mathbf{X_2}$	$\mathbf{X_3}$	$\mathbf{X_4}$	$\mathbf{logX_4}$	$\mathbf{X_5}$
Skewness	5,80	0,23	-0,78	0,61	2,44	8,90	0,84	1,57
Kurtosis	40,27	0,27	3,59	0,61	8,04	78,30	2,65	2,55



(a)	(b)

Figure 2. Boxplot of the Response and Explanatory Variables:
(a) Original data and (b) with logarithmic transformation

The map from Figure 3 shows the spatial distribution of district/city-level GRDP across Indonesia, revealing a clear spatial pattern: high GRDP values are concentrated primarily on the island of Java especially in the Jakarta metropolitan area and Surabaya whereas eastern regions of Indonesia generally exhibit lower GRDP. On the map, darker shades represent higher GRDP, while lighter shades indicate lower GRDP. This pattern reflects pronounced spatial disparities in economic development across districts/cities.

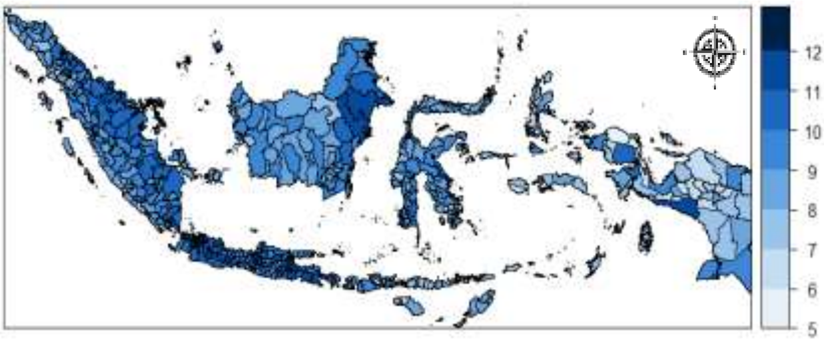


Figure 3. Thematic Map of the Log GRDP (Non-Scale Map)

The correlations among the response variable and the explanatory variables are presented in Figure 4. Human development index (X_1), number of workers (X_3) and original local government revenue (X_4) exhibit positive correlations with logY (GRDP), with coefficients of $r = 0{,}55$, $r = 0{,}82$ and $r = 0{,}87$, respectively. This indicates that regions with a higher human development index, number of workers, and original local government revenue tend to have greater GRDP. Conversely, the poverty rate (X_5) is negatively correlated with GRDP (Y), suggesting that areas with a high poverty percentage are associated with lower GRDP levels. Meanwhile, the district/city minimum wage shows a weak correlation ($r = 0.02$). According to Syam et al. (2025), this indicates that while the direct effect of this explanatory variable on the response variable may be insignificant, it may play an indirect role within a broader context.

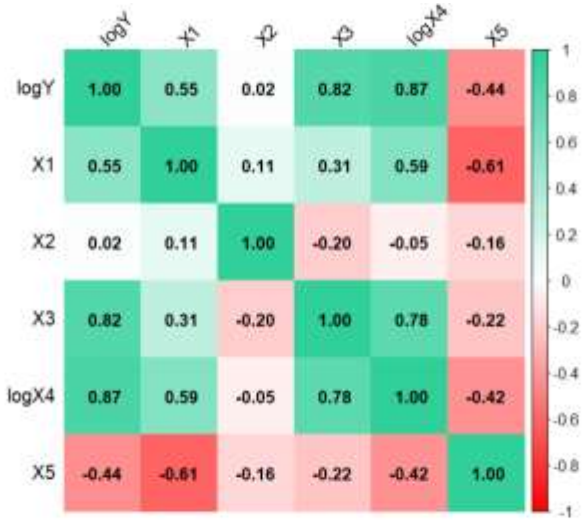


Figure 4. Correlation Plots illustrating the Relationship between the Response Variable and the Explanatory Variables

2. Identification of Multicollinearity

Multicollinearity emerges when explanatory variables in a regression model are highly correlated with each other. This phenomenon can cause variables that are theoretically significant to appear statistically insignificant (Shrestha, 2020), thereby leading to unreliable regression estimates. Hence, it is important to examine the presence of multicollinearity, typically by computing the Variance Inflation Factor (VIF). An explanatory variable is considered to exhibit substantial multicollinearity if its VIF exceeds 5 (Marcoulides & Raykov, 2019). The VIF values are presented in Table 3. The multicollinearity assessment based on the VIF results in Table 3 indicates that all VIF values are below 5, suggesting that no multicollinearity is present among the explanatory variables.

Table 3. VIF Values of the Explanatory Variables

Variables	$\mathbf{X_1}$	$\mathbf{X_2}$	$\mathbf{X_3}$	$\mathbf{logX_4}$	$\mathbf{X_5}$
VIF Value	2,76	1,05	2,21	3,48	2,08

3. Spatial Weight Matrix

Spatial weight matrix generally represents the spatial relationships or proximity among regional units, such as between districts or cities. The spatial weight matrices considered in this study include distance-based weighting schemes: the k-nearest neighbors (KNN) matrix, the distance-threshold matrix, the inverse-distance matrix, and the exponential-distance matrix. The parameters of these weight matrices are subsequently optimized. Model evaluation is then conducted by identifying the matrix that yields the highest and statistically significant of Moran's I. The selected spatial weight matrix is the one associated with the largest Moran's I value—specifically, the exponential-distance matrix with a distance decay parameter $\omega = 1,5$. The exponential distance weight value is expressed as follows:

$$w_{ij} = \exp\left(-\omega d_{ij}\right) \tag{12}$$

where ω is a positive number

Table 4. Summary of the Parameter Optimization Results for the Spatial Weight Matrix

Weight Matrix	**Parameter**	**Moran Index**	**p-value**
KNN	$k = 6$	0,60	$< 2,2 \times 10^{-16}$
Distance band	$d_{max} = 120$	0,54	$< 2,2 \times 10^{-16}$
Inverse distance	$\alpha = 2$	0,51	$< 2,2 \times 10^{-16}$
Exponential distance	$\omega = 1,5$	0,64	$< 2,2 \times 10^{-16}$

4. Identification of Spatial Effects

Spatial effects in data typically arise from spatial dependence and spatial heterogeneity. Spatial dependence indicates that the observation at one location is influenced by observations at neighboring locations. In contrast, spatial heterogeneity refers to non-constant error variance across locations, often resulting from differences in underlying characteristics among observational units. To test for spatial dependence, Moran Index was computed using an exponential distance-based spatial weight matrix ($\omega = 1,5$) applied to the response variable.

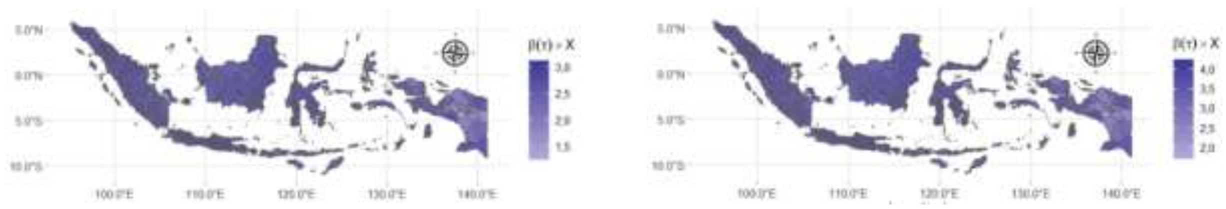
As shown in Table 5, the resulting p-value is less than the significance level ($\alpha = 0{,}05$), and Moran Index statistic is positive, indicating the presence of positive spatial dependence among observations. Spatial heterogeneity was assessed using the Breusch–Pagan test. Table 5 reports a p-value below the 5% significance level, leading to the conclusion that spatial heterogeneity is present in the data. Collectively, the diagnostic results in Table 5 provide strong evidence of both spatial dependence and spatial heterogeneity, confirming the existence of significant spatial effects in the dataset.

Table 5. Results of the Spatial Effects Tests

Test	Test Statistics	p-value	Conclusion
Moran Index	0,64	$< 2{,}2 \times 10^{-16}$	There is spatial dependence
Breusch-Pagan	73,58	$1{,}8 \times 10^{-14}$	There is spatial heterogeneity

5. Estimation of SF-UQR Parameters

The parameter estimates for the SF-UQR model are summarized in Table 6. Variable X_1 (human development index) exhibits a positive and statistically significant effect at quantiles 0,75 and 0,9. The effect is stronger at quantile 0,9 than at quantile 0,75, indicating distributional heterogeneity. Regions with higher HDI display larger contributions to the upper GRDP distribution (reflected by darker colors). However, these findings are interpreted within the framework of aggregate distributional relationships. From a policy perspective, HDI should be integrated with broader regional economic strengthening strategies to promote inclusive growth and prevent widening regional disparities.



(a) (b)

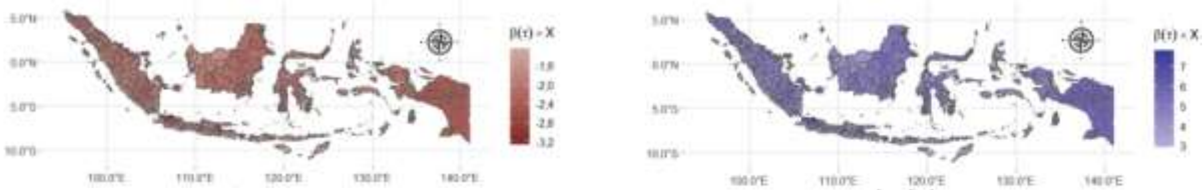
Figure 5. Spatial Distributional of Significant HDI Contribution to the GRDP Distribution: (a) at Quantile 0,75; and (b) at Quantile 0,9 (Non-Scale Map)

Table 6. Parameter Estimates of the SF-UQR Model

Variables	Parameter	Quantile				
		0,1	**0,25**	**0,5**	**0,75**	**0,9**
Intercept	β_0	6,1*	6,3*	7,2*	4,3*	$1{,}6\times10^{-1}$
X_1	β_1	$2{,}9\times10^{-2}$	$9{,}8\times10^{-3}$	$-4{,}9\times10^{-3}$	$3{,}5\times10^{-2}$*	$4{,}8\times10^{-2}$*
X_2	β_2	$-6{,}3\times10^{-1}$*	$-3{,}5\times10^{-1}$*	$-2{,}1\times10^{-1}$*	$3{,}1\times10^{-1}$*	1,5*
X_3	β_3	$-3{,}6\times10^{-7}$	$8{,}3\times10^{-8}$	$1{,}1\times10^{-6}$*	$2{,}7\times10^{-6}$*	$3{,}7\times10^{-6}$*
$\log X_4$	β_4	$4{,}8\times10^{-1}$*	$6{,}2\times10^{-1}$*	$5{,}9\times10^{-1}$*	$2{,}7\times10^{-1}$*	3×10^{-1}*
X_5	β_5	$-8{,}2\times10^{-2}$*	$-6{,}3\times10^{-2}$*	-2×10^{-2}	$1{,}5\times10^{-2}$	$1{,}4\times10^{-2}$

*significant at $\alpha = 0{,}05$

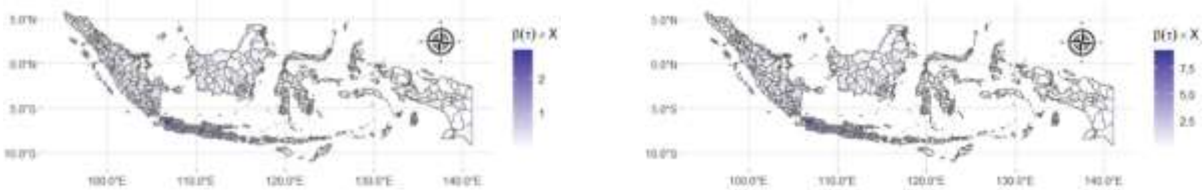
In contrast, the minimum wage is statistically significant across all analyzed quantiles of the GRDP distribution, although the direction of the association differs. It is negatively associated with GRDP distribution at the lower and median quantiles and positively associated at the upper quantiles, indicating pronounced distributional heterogeneity. Darker shades in the map reflect stronger contributions consistent with the sign of the coefficient. The negative association in the lower segment may reflect cost-side pressures linked to higher labor expenses and constrained labor absorption, whereas the positive association in the upper segment may align with stronger productivity and absorptive capacity. These patterns suggest that minimum wage considerations may need to be aligned with underlying economic structures and complemented by productivity-enhancing efforts, particularly within the lower and median segments of the GRDP distribution, as shown in Figure 6.



(a) (b)

Figure 6. Spatial Distributional of Significant minimum wage contribution to the GRDP distribution: (a) at quantile 0,1; and (b) at quantile 0,9 (Non-Scale Map)

Meanwhile, variable X_3 (number of workers) is insignificant at low quantiles but becomes positive and statistically significant at median to upper quantiles (0,5, 0,75, and 0,9), indicating that its association with GRDP varies across the distribution. The stronger contribution observed at the upper quantiles suggests that the worker–output relationship is not uniform across distributional segments. This pattern may reflect differences in economic structure, productivity levels, and labour absorption capacity across segments of the GRDP distribution, as highlighted by Andriansyah et al. (2023). In higher segments, the number of workers appears more closely aligned with higher value-added activities, whereas in the lower segment the absence of statistical significance may indicate structural productivity constraints or limited absorptive capacity. These findings describe aggregate distributional patterns within the GRDP distribution. Such patterns suggest that variations in the number of workers may need to be considered alongside structural economic conditions and productivity capacity to support more balanced outcomes across the distribution. Enhancing workforce quality and strengthening productive sector absorption, particularly within segments where the association is weaker or statistically insignificant, may contribute to a more even alignment between employment levels and overall economic performance, as shown in Figure 7.



(a) (b)

Figure 7. Spatial Distributional of Significant Number of Workers Contribution to the GRDP Distribution: (a) at Quantile 0,5; and (b) at Quantile 0,9 (Non-Scale Map)

Furthermore, the log-transformed variable X_4 (original local government revenue) is positive and statistically significant across all quantiles. Although the magnitude of its contribution varies, the direction remains consistently positive, indicating that the linkage between local fiscal capacity and economic performance is present throughout the distribution. Darker shades on the map represent larger distributional contributions consistent with the sign of the coefficient at each quantile. Within this aggregate distributional framework, the consistent positive association suggests that local fiscal capacity may align with economic dynamics across different segments of the GRDP distribution. Accordingly, strengthening the original local government revenue base and enhancing the effectiveness of local fiscal management may be considered as part of broader efforts to promote more balanced regional economic dynamics, while accounting for structural differences across regions, as shown in Figure 8.

(a) (b)

Figure 8. Spatial Distributional of Significant Original Local Government Revenue Contribution to the GRDP Distribution: (a) at Quantile 0,1; and (b) at Quantile 0,9 (Non-Scale Map)

Finally, variable X_5 (poverty rate) exhibits a negative and statistically significant effect like study Zhu et al. (2022) at low quantiles (0,1 and 0,25) but becomes insignificant at median and upper quantiles, indicating pronounced distributional heterogeneity. Darker shades on the map represent stronger negative distributional contributions. These findings suggest that poverty dynamics are particularly relevant in the lower segment of the GRDP distribution, highlighting the importance of addressing structural economic constraints in lower-income regions to support more balanced regional economic dynamics, as shown in Figure 9.

(a) (b)

Figure 9. Spatial Distributional of Significant Poverty Rate Contribution to the GRDP Distribution: A at Quantile 0,1 and B at Quantile 0,25 (Non-Scale Map)

6. Model Evaluation

Model evaluation is essential to assess how well the regression model captures the relationship or influence between explanatory and response variables. In this study, the coefficient of determination, specifically the adjusted R^2, is employed as the primary goodnessof-fit measure. Table 7 presents the adjusted R^2 values for the SF-UQR model alongside those of the standard UQR for comparative purposes.

Table 7. Evaluation of the SF-UQR Model

Model	Quantile				
	0,1	**0,25**	**0,5**	**0,75**	**0,9**
UQR	0,38	0,43	0,46	0,52	0,5
SF-UQR	0,6	0,65	0,59	0,67	0,56

Across all quantiles analyzed, the SF-UQR model consistently yields higher adjusted R^2 values than the standard UQR model, indicating an improved proportion of the marginal quantile variation in the response variable Y explained by the model. The highest adjusted R^2 value, 0,67, is achieved at the 0,75 quantile. This implies that 67% of the marginal quantile variation in Y is accounted for by the model, while the remaining 33% is attributed to factors outside the model. These results confirm that incorporating a spatial filtering component enhances the model's explanatory power. Consistent with Vogt & Fochezatto (2023), incorporating spatial autocorrelation into UQR analysis is important for adequately capturing complex relationships among variables. In general, the results of this study are consistent with the findings of Sahputri et al. (2022), who reported that the HDI, original local government revenue, and the number of workers have positive effects on economic growth. Furthermore, the negative association between the poverty rate and economic growth identified in this study aligns with the findings of Zhu et al. (2022).

D. CONCLUSION AND SUGGESTIONS

The parameter estimates from the SF-UQR model exhibit quantile-specific heterogeneity across several explanatory variables. The human development index exerts a positive and statistically significant effect at high quantiles but insignificant at low and median quantiles. The minimum wage is statistically significant across all quantiles; however, its impact is negative from the lower to median quantiles and reverses to positive at the upper quantiles. The number of workers shows a positive and significant effect only at the median to upper quantiles. Original local government revenue is consistently positive and significant across all quantiles. Finally, the poverty rate has a negative and significant effect exclusively at the lower quantiles.

Collectively, these results indicate that regional economic dynamics are shaped by structurally differentiated mechanisms across the distribution rather than uniform effects. The superior performance of the SF-UQR model relative to the standard UQR model further confirms the importance of accounting for spatial autocorrelation in capturing complex regional relationships. Taken together, the evidence suggests that strategies aimed at strengthening human capital, improving labour productivity, enhancing fiscal capacity, and addressing poverty-related structural constraints may need to be aligned with the distributional position and structural characteristics of regions in order to support more balanced and inclusive regional economic dynamics.

Despite its contributions, this study is limited by the scope of explanatory variables included in the model, as the analysis focuses on selected socioeconomic indicators and does not explicitly incorporate structural transformation measures, infrastructure development, investment intensity, or sectoral composition that may also influence regional economic disparities. Consequently, the estimated relationships should be interpreted within the context of the specified variables. Future research is therefore encouraged to broaden the set of explanatory factors by integrating structural and sectoral indicators as well as infrastructure and investment measures to provide a more comprehensive understanding of heterogeneous regional economic dynamics and to strengthen the empirical foundation of regional economic analysis.

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