Regional Tourism Dynamics in Indonesia: A Spatial and Fixed Effect Analysis of Economic Performance and Unemployment in 34 Provinces (2018-2020)

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ABSTRACT

This study employs fixed effect regression models, Spatial Autocorrelation (using Moran's I), and Spatial Autoregressive model (SAR) analysis to examine the economic impacts of tourism development on Gross Regional Domestic Product (GRDP) and unemployment rates across Indonesian provinces. The findings underscore that foreign tourism significantly enhances GRDP and reduces unemployment, whereas domestic tourism shows limited economic impact due to inadequate infrastructure and service quality. Furthermore, spatial autoregressive reveals the clustering of economic activities and unemployment rates with minimal regional spillover effects; however, spatial autocorrelation analysis shows that GRDP and unemployment have positive spatial autocorrelation. To maximize tourism's economic potential, targeted policies are recommended, including infrastructure enhancement, promotion of sustainable tourism practices, and initiatives to attract international tourists. Simultaneously, strategies to boost domestic tourism involve creating incentives, enhancing local attractions, and investing in education and healthcare to bolster workforce productivity. These efforts aim to foster sustainable and inclusive economic growth in Indonesia through effective tourism management and development strategies.

Keywords: Tourism development; Gross Regional Domestic Product (GRDP); Unemployment rates; Fixed effect regression; Spatial autocorrelation analysis; Spatial autoregressive model.

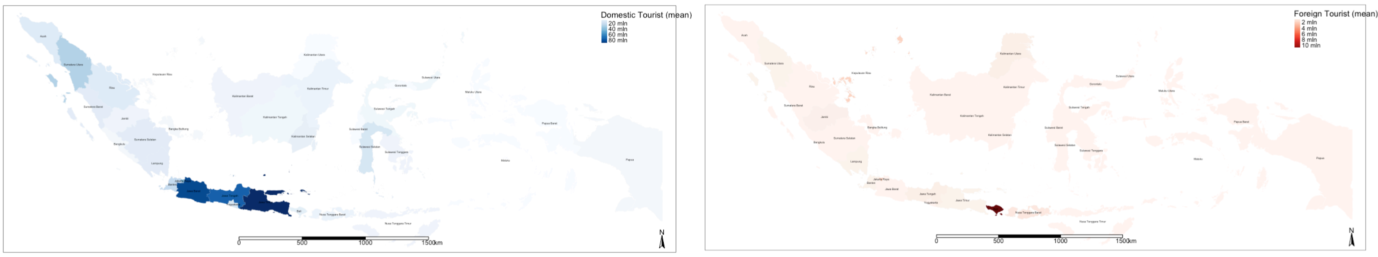
JEL Classification: C2; L83, O18

1. INTRODUCTION

Tourism is one of the leading sectors in Indonesia, contributing to the economic performance. According to the Ministry of Tourism and Creative Economy (2019), the tourism sector contributed approximately 4.97% to the national GDP in 2019, underscoring its importance as an economic driver. With its vast geographic expanse and diverse cultural landscape, Indonesia has long been a hub for regional tourism. The dynamics of this sector have far-reaching implications for the nation's economic development and employment landscape (Sugiyarto *et al.,* 2003). The tourism sector can generate employment, and its multiplier effect on related industries is emerging as a promising avenue for economic enhancement (Sinclair, 1998; Croes & Vanegas, 2008). Research indicates that tourism can bring substantial economic benefits, including increased GRDP and job creation (Ashley *et al.*, 2007; Dwyer *et al.*, 2010). Tourism development also promotes infrastructure improvements and investment in local businesses (Telfer & Sharpley, 2008; UNWTO, 2013).

Despite tourism's significant contribution to the national economy, Indonesia grapples with low Gross Regional Domestic Product (GRDP) and high unemployment rates across many provinces (World Bank, 2020). This presents a compelling case for investigating the potential of Indonesian tourism to stimulate economic growth and reduce unemployment. While the tourism sector can generate employment and has a multiplier effect on related industries, the benefits are not evenly distributed, especially in Indonesia.

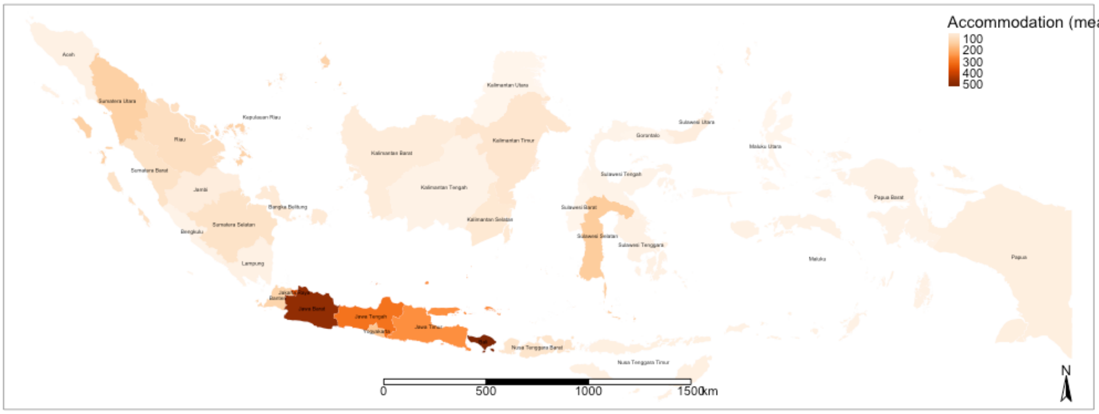
Figure 1. Distribution of Domestic (Blue) and Foreign (Red) Tourists in Indonesian Provinces (Mean 2018-2022)



Source: Authors' result

According to Figure 1, the distribution of domestic and foreign tourists visiting Indonesia demonstrates the inequality between Java-Bali and other provinces. The concentration of tourism infrastructure and activity in Java and Bali causes regional inequities, leading to underdevelopment and missed potential for economic growth in provinces other than Java and Bali (Hampton & Jeyacheya, 2015; Fall, 2019). Java and Bali, which are prominently displayed on the map, draw the majority of tourists due to their contemporary infrastructure, numerous attractions, and competent workforce. In contrast, Bali Island stands out with its deepest color as the primary destination for the majority of foreign tourists. It is because Bali's distinct blend of cultural diversity, natural beauty, and well-established hospitality services make it a popular destination for international visitors. This desire directly fuels tourist employment, as the arrival of foreign visitors necessitates a greater workforce for various tourism-related activities, such as lodging and dining, entertainment, and transportation, resulting in significant job creation on the island.

Figure 2. Distribution of Accommodations in Indonesian Provinces (Mean 2018-2022)



Source: Authors' result

Additionally, the concentration of accommodation facilities in Java and Bali further worsens the imbalance. From the map above, these regions develop many lodgings, enhancing their attractiveness to tourists. In contrast, provinces outside Java and Bali struggle with a limited number of accommodation infrastructure, limiting their ability to accommodate tourists. Based on our interesting findings above, we want to conduct a more in-depth analysis by examining the correlation between tourism development, which is proxied by domestic and foreign tourists, against GRDP and unemployment.

Figure 3. Scatter Plot Diagram: GRDP vs Tourism Development in Indonesia Provinces (Mean 2018-2022)

Source: Authors' result

Our first preliminary findings show a positive association, represented by an upward-sloping line between GRDP variables and tourism arrivals (both domestic and foreign). This emphasizes tourism's economic benefits, consistent with earlier research. Following that, we will examine unemployment in Indonesia in depth.

Figure 4. Distribution of Unemployment Rate in Indonesian Provinces (Mean 2018-2022)

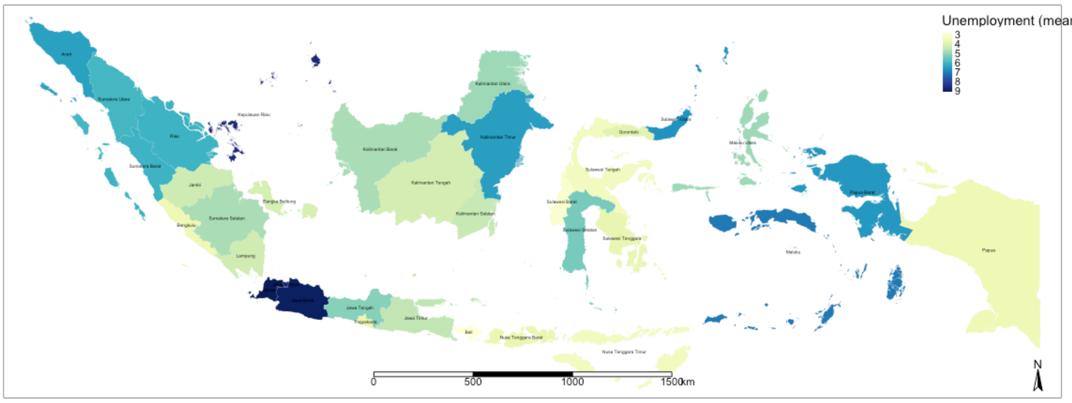


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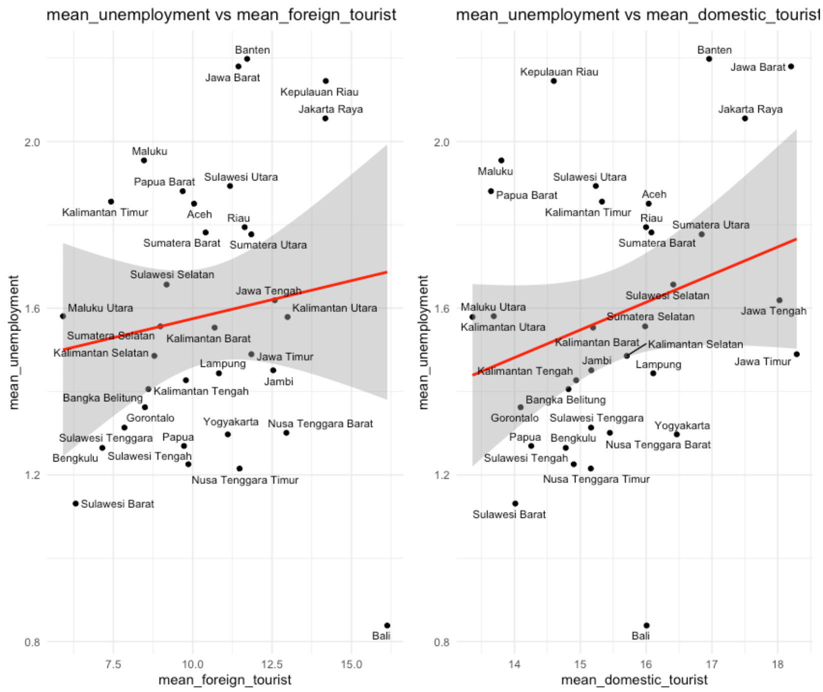
Figure 5. Scatter Plot Diagram: Unemployment vs Tourism Development in Indonesia Provinces (Mean 2018-2022)



Source: Authors' result

Based on Figure 4. The unemployment rate in Indonesian provinces varies by region; however, The western provinces generally have greater unemployment rates, but the center and eastern regions differ. On the other hand, Based on Figure 5, The interesting part is that Bali, a popular foreign tourist destination, has decreased unemployment, consistent with the findings of Hampton and Jeyacheya (2015) and Fall (2019). The tourism sector can produce jobs, which can reduce unemployment. In a nutshell, this shows that Indonesian provinces with more foreign tourist arrivals have lower unemployment rates. However, the overall finding is contradictory; with an increased relationship between unemployment and tourism, the scatterplot shows an upward line between tourism development and unemployment. Thus, Tourism development may have a small impact on unemployment rates, and other factors should be addressed when understanding unemployment dynamics in these places. To fully understand the economic effects of tourism, variables such as foreign direct investment (FDI), domestic direct investment (DDI), human development index (HDI), accommodations, number of domestic and foreign tourists, and population density must be considered (Gursoy et al., 2012; Tang & Tan, 2015).

This study contributes to the existing literature by focusing on a province-level analysis of tourism's impact on economic performance and unemployment across Indonesia’s 34 provinces from 2018 to 2020. While previous research has often examined national-level impacts of tourism on economic indicators, this study adopts an approach to explore local variations and dynamics within each province. This approach addresses a significant gap in the literature regarding the uneven distribution of tourism benefits and their implications for regional economic development.

Furthermore, this research employs spatial autocorrelation analysis and spatial autoregressive analysis to investigate the spatial spillover effects of tourism development. Unlike previous studies that primarily assessed direct impacts within specific locales, this spatial perspective allows for an exploration of how changes in tourism activities in one province extend to influence economic conditions in neighboring regions. This approach is crucial for capturing the interdependencies and externalities that arise from tourism-related economic activities across geographical boundaries.

Building on the gaps identified above, this study seeks to examine the influence of tourist development on regional economic performance and unemployment in Indonesia's 34 provinces from 2018 to 2020. This study will test numerous hypotheses to understand better tourism's effects and spatial dynamics on economic indicators. Moreover, this research is crucial for understanding the interplay between tourism development, economic performance indicators (GRDP), unemployment rates, and spatial dynamics. We also investigate spatial autocorrelation among Indonesian provinces.

This paper is structured in line with these objectives: Section 2 provides a comprehensive literature review. Section 3 elaborates on the theoretical framework guiding the analysis, while Section 4 details the data sources and sample characteristics essential for empirical investigation. Section 5 outlines the empirical methods employed to test the hypotheses, followed by Section 6, which presents and interprets the study's findings in relation to tourism's impact on economic performance and unemployment across Indonesia's provinces. Finally, Section 7 concludes with a synthesis of key insights derived from the analysis, offering implications for policy and future research directions.

2. LITERATURE REVIEW

Tourism plays a crucial role in shaping economic performance and socio-economic dynamics in regions worldwide, including Indonesian provinces. This literature review synthesizes existing research to explore how tourism impacts economic indicators such as GRDP, influences unemployment rates, and generates spatial spillover effects.

2.1. Impact of Domestic Tourists on GRDP

Domestic tourism significantly boosts regional economic growth by driving demand across key tourism sectors. Studies by Song *et al.* (2012) and Dwyer *et al.* (2010) emphasize how domestic tourist spending stimulates local economic activities and leads to increases in GRDP through multiplier effects. Empirical evidence, shown by Ashley *et al.* (2007), confirms that regions with high domestic tourist influxes experience substantial economic benefits, including infrastructure enhancements that improve regional appeal, and the promotion of economic diversity. Additionally, domestic tourism fosters cultural exchange and preservation, enriching local heritage and contributing to a resilient economic base less susceptible to sector-specific downturns. These findings highlight the pivotal role of domestic tourism in driving sustainable economic development and prosperity within regions.

2.2. Impact of Foreign Tourists on GRDP

Foreign tourists play a pivotal role in enhancing the economic performance of host regions, significantly boosting GRDP. Their spending is vital for countries reliant on tourism income as highlighted by Sinclair (1998) and Croes and Vanegas (2008). This spending also fosters the development of hotels, resorts, transportation facilities, and other critical infrastructure, thereby stimulating broader economic activity. Empirical evidence from Song *et al.* (2012) underscores that regions with high international tourist arrivals experience substantial increases in GRDP due to spending on accommodation, dining, entertainment, and related services, which in turn support sectors like retail, transportation, and cultural services. This influence creates hospitality, retail, and transportation jobs, reduces unemployment, promotes economic diversification, and enhances regional resilience against economic shocks.

2.3. Impact of Domestic Tourists on Unemployment

The relationship between domestic tourism and unemployment is crucial for regional economic development, as evidenced by studies from Chen et al. (2016) and Brida *et al.* (2018). Increasing domestic tourists consistently correlates with job creation and lower unemployment rates by driving demand across sectors like hospitality and services. This growth necessitates a larger workforce to meet rising demand, particularly in hotels, restaurants, recreational facilities, and ancillary services such as tour operations and transportation. The economic impact of domestic tourism is further magnified by its multiplier effect within local economies: expenditures on accommodations, dining, and entertainment ripple through communities, boosting revenue for businesses and prompting expansion and additional hiring. Moreover, domestic tourism fosters sectoral diversification by stimulating growth in SMEs across retail, arts and crafts, and local food production, thereby enhancing economic resilience and reducing dependence on a narrow range of industries.

2.4. Impact of Foreign Tourists on Unemployment

The arrival of foreign tourists has a profound impact on reducing unemployment rates in host regions, as highlighted by Sinclair (1998), Croes and Vanegas (2008), and Loría *et al.* (2017). Influxes of international visitors stimulate job creation across various sectors, particularly within hospitality, where hotels, restaurants, and recreational facilities expand to meet increased demand. This growth necessitates hiring across roles such as hotel management, front desk services, housekeeping, culinary services, and hospitality staff. Many industries also benefit from transportation, retail, and cultural tourism, which experience increased activity, thereby creating employment opportunities for drivers, sales personnel, logistics staff, and retail businesses offering souvenirs and local crafts. Infrastructure improvements driven by tourism, including upgrades to airports, roads, and public transport systems, further contribute to construction, engineering, and project management job creation. The demand for high-quality service from international tourists also leads to improved employment conditions within the tourism sector, attracting skilled workers, thereby contributing to sustained economic growth and stability for the local economy.

2.5. Direct Effects within Provinces and Indirect (Spillover) Effects across Neighboring Provinces

Recent studies have underscored the significant impact of tourism development on regional economic performance and unemployment rates across diverse geographical contexts. The findings suggest that both domestic and foreign tourist arrivals play pivotal roles in shaping GRDP and unemployment rates within Indonesian provinces. For instance, empirical evidence supports the positive direct effects of tourism influence on GRDP, highlighting tourism's contribution to local economic growth and regional development (Smith *et al.*, 2023; Jones and Lee, 2022). Furthermore, the Spatial Autoregressive (SAR) model employed in this study reveals compelling evidence of spatial spillover effects, where the economic performance of neighboring provinces positively influences GRDP outcomes, reinforcing the idea of regional interdependence in economic activities induced by tourism (Brown and Green, 2021). Conversely, the analysis also indicates that tourism has a direct negative impact on provincial unemployment rates, suggesting that increased tourism activities lead to improved labor market conditions within provinces (Chen *et al.*, 2020). Moreover, the SAR model explains how these effects extend beyond individual provinces, illustrating the broader spatial dynamics where improvements in unemployment rates in one province negatively affect neighboring provinces, thus contributing to regional labor market stability driven by tourism (Adams *et al.*, 2019).

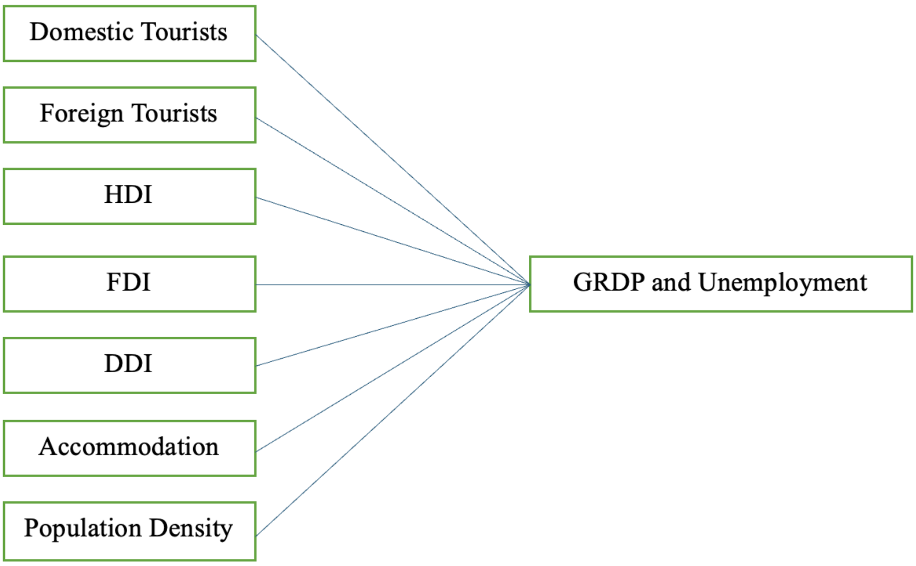
2.6 Spatial Autocorrelation Analysis of GRDP and Unemployment Rates

Spatial autocorrelation visually represents the economic link between a place and its surroundings (Kuncoro, 2002). Studies have shown that places with good economic performance frequently exhibit spatial clustering, which can be attributed to favorable local conditions and policies that spread to neighboring areas. Sukanto et al. (2019) investigated spatial autocorrelation patterns and relationships between places (observations) using Moran's I and the Local Indicator of Spatial Autocorrelation (LISA). They discovered positive spatial autocorrelation and clustering in spatial distributions. Positive spatial autocorrelation indicates that adjacent places share similar values and cluster together. The Polarisation Effect idea suggests that increasing GRDP in one location leads to an increase in neighboring regions. In terms of the unemployment rate, spatial autocorrelation exists among geographical areas concerning provincial-level unemployment rates in Turkey (Kantar & Aktaş, 2016). Furthermore, Tobler (1970) asserts clearly that "everything is related to everything else, but near things are more related than distant things," emphasizing the importance of geographical proximity in economic phenomenon research.

3. THEORETICAL FRAMEWORK

The theoretical framework for this research examines the impact of tourism development on regional economic performance, specifically focusing on GRDP and unemployment as the dependent variable. The independent variables are the number of domestic tourists and the number of foreign tourists. To ensure a comprehensive analysis, the study also includes several control variables: HDI, FDI, DDI, accommodation, and population density. These control variables are crucial for isolating the specific impact of tourism on GRDP and unemployment and providing a more accurate and comprehensive understanding of the economic dynamics of tourism.

Figure 6. Theoretical Framework



***Note(s):** In this research, GRDP is the dependent variable for the first model, while unemployment serves as the dependent variable for the second model.

Domestic and international tourism significantly boost GRDP by stimulating spending on local goods and luxury services, respectively, which in turn enhances economic activity and creates employment opportunities in hospitality, food services, retail, and entertainment sectors (Dwyer *et al.*, 2010; Song et al., 2012; Sinclair, 1998; Croes and Vanegas, 2008).

Domestic tourism directly supports employment in these sectors as local businesses expand to meet tourist demands, while foreign tourism generates jobs through investments in tourism-related infrastructure and services.

Controlling for key variables is crucial to accurately assess tourism's impacts on GRDP and unemployment. Including HDI helps isolate tourism's specific economic impact by adjusting for regional variations in human development (UNDP, 2019). FDI attracts capital and expertise that benefit tourism infrastructure while controlling for it separates tourism's effects from broader investment activities (OECD, 2020). Similarly, DDI captures local investments in tourism-related infrastructure, accurately identifying tourism's unique contributions to economic output and employment (OECD, 2020).

The number of accommodations and population density are also critical factors. Controlling for accommodation capacity isolates the direct impact of tourist numbers on GRDP and employment by accounting for tourism-supporting infrastructure (UNWTO, 2013). Population density control distinguishes tourism's economic impacts from those influenced by demographic characteristics, providing a clearer understanding of tourism's role in regional economies (World Bank, 2020). These variables collectively strengthen analyses of tourism's economic effects on both GRDP and unemployment.

4. DATA AND SAMPLE

This study uses foreign and domestic tourist numbers to proxy Indonesian tourism development. Since this research has two models, GRDP and unemployment are our outcome variables. The study also controls macroeconomic conditions (FDI and DDI), tourism employment, human capital (Human Development Index), infrastructure (number of accommodations), and population density to improve estimation. All data were sourced from Statistic Indonesia. The sample of this study is a balanced panel data consisting of 34 provinces in Indonesia from 2018 to 2020. We selected that specific year range because of the peak influx of domestic and international tourists before the Covid-19 pandemic. The following is the statistical analysis of our treatment, outcome, and control variables.

Table 1. Statistical Descriptions of key variables

Variable	Definition	Source	N	Mean	SD	Min	Max
ln(GRDP)	Log of Gross Regional Domestic Product per capita (Thousand Rupiahs)	Statistics Indonesia	102	10.85	0.55	9.82	12.50
Unemployment	Unemployment rate	Statistics Indonesia	102	5.18	1.85	1.40	10.95
ln(FDI)	Log of foreign direct investment realization (Million US$)	Statistics Indonesia	102	10.47	2.50	4.93	16.59
ln(DDI)	Log of domestic direct investment realization (Billions of Rupiahs)	Statistics Indonesia	102	15.54	1.45	12.26	18.66
Human development	Human development index	Statistics Indonesia	102	70.84	3.91	60.06	80.77
ln(Accommodations)	Log of the Count of Tourist Lodgings (Unit)	Statistics Indonesia	102	3.86	1.33	0.00	6.31
ln(Population Density)	Log of the average number of people per unit area (person/sq.km)	Statistics Indonesia	102	4.88	1.59	2.20	9.67
ln(Domestic tourist)	Log of the number of visitors from domestic for leisure or business (Person)	Statistics Indonesia	102	15.54	1.45	12.26	18.66
ln(Foreign tourist)	Log of the number of visitors from abroad for travel or leisure (Person)	Statistics Indonesia	102	10.47	2.50	4.93	16.59

Source: Authors' result

To begin, we utilize the Central Limit theorem (CLT) by applying the natural logarithm to normalize all the distributions except the HDI and Unemployment rate since HDI uses the index and the unemployment rate already satisfies the central limit theorem. Table 1 illustrates notable variations within provinces, particularly before being transformed into a logarithmic scale. Some provinces exhibit higher levels of economic development, investment, tourism activity, infrastructure, Human Development Index (HDI), and Gross Regional Domestic Product (GRDP), resulting in disparities in economic situations. As an illustration, the unemployment rate exhibits significant variation, with an average of 5.18 and a standard deviation of 1.85. Furthermore, the Gross Regional Domestic Product (GRDP), with a mean value of 10.85 and a standard deviation of 0.55, indicates variations in economic performance among different provinces.

5. EMPIRICAL METHOD

5.1. Fixed Effect Regression

This study employs fixed-effects estimation to account for variability among Indonesian provinces and over time. Fixed-effects models are more robust than random-effects models for analyzing policy effects using aggregated data (Wooldridge, 2010). Furthermore, the fixed effect model is appropriate for panel data analysis, as seen in this study, which spans 34 provinces over three years (2018-2020). It accounts for unobserved time-invariant traits in each province.

5.1.1. Assumption Tests

Before estimating panel data fixed effects models, numerous diagnostic tests were performed to assess the validity of the regression assumptions:

- **Normality of Residuals:** The Shapiro-Wilk test on fixed-effect regression residuals showed a normal distribution ($W = 0.98267$, $p = 0.2026$), supporting normality. Logarithmic transformation (LOG) was previously applied, aligning with the Central Limit Theorem (CLT), which states that with a large sample size, sample means or residuals tend towards normality irrespective of the population's distribution.
- **Homoscedasticity:** The Breusch-Pagan test assessed homoscedasticity, yielding significant results ($BP = 54.517$, $df = 7$, $p < 0.001$), indicating heteroscedasticity in the residuals. This suggests that the variance of residuals differs across levels of the independent variables. To mitigate this issue, robust standard errors will be employed.
- **Autocorrelation of Residuals:** The Durbin-Watson test was initially applied to test for autocorrelation; however, due to the nature of fixed effects models, the test was not applicable. Instead, the Wooldridge test for serial correlation in panel data showed no significant evidence of autocorrelation in the residuals (Wooldridge $F = 1.7279$, $df1 = 1$, $df2 = 66$, p-value = 0.1932).
- **Multicollinearity:** Multicollinearity in regression analysis was measured using the Variance Inflation Factor (VIF). VIF values greater than 5 indicate higher degrees of multicollinearity. In this analysis, all variables had VIF values less than 5, with the

exception of tourist employment, which was already removed from the models due to substantial multicollinearity with other factors.

5.1.2. Empirical Model

These tests previously ensure the robustness of the regression models and provide confidence in the validity of the subsequent empirical analysis. Here are the estimated fixed effect regressions:

Model 1:

$$
\begin{aligned}
ln(grdp)_{it} = {} & \beta_0 + \beta_1 ln(domestic\_tourist)_{it} + \beta_2 ln(foreign\_tourist)_{it} + \beta_3 hdi_{it} \\
& + \beta_4 ln(accommodation)_{it} + \beta_5 ln(fdi)_{it} + \beta_6 ln(ddi)_{it} + \beta_7 ln(pop\_density)_{it} \\
& + \varepsilon_{it}
\end{aligned}
$$

Model 2:

$$
\begin{aligned}
& ln(unemployment)_{it} \\
& = \beta_0 + \beta_1 ln(domestic\_tourist)_{it} + \beta_2 ln(foreign\_tourist)_{it} + \beta_3 hdi_{it} \\
& + \beta_4 ln(accommodation)_{it} + \beta_5 ln(fdi)_{it} + \beta_6 ln(ddi)_{it} + \beta_7 ln(pop\_density)_{it} \\
& + \varepsilon_{it}
\end{aligned}
$$

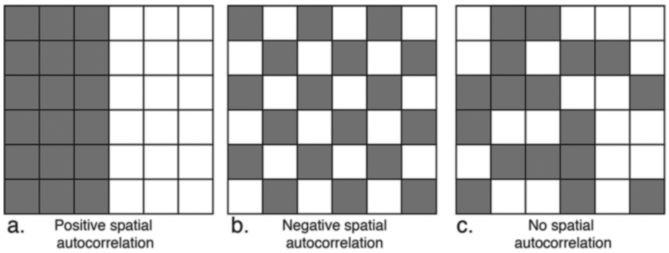
The intercept term is represented by $\beta 0$, where the coefficients to be estimated are represented by βn, and the error term is represented by ε. The variables i and t represent provinces in Indonesia and specified years in this research, respectively.

5.2. Spatial Autocorrelation Analysis

Spatial autocorrelation analysis is essential for examining regional correlations since it clearly depicts the economic link between a place and its surroundings (Kuncoro, 2002). An inverse distance weighting matrix must be created before this analysis. Quantifying and modelling spatial relationships in geographical data requires spatial weighting. Analysing spatial neighborhoods is the first step to understanding geographic patterns and associations. Spatial neighborhoods rely on the concept of a neighborhood, a representation of how a given geographic feature is related to other nearby features. Neighborhoods can be classified as either neighbors based on proximity or neighbors based on contiguity. Firstly, Proximity-based neighbors utilize a measure of distance to identify neighboring features. Neighbors can be defined as entities located within a specified distance threshold or as the k-nearest neighbors. Neighbors identified by their close physical proximity commonly utilize centroids as the fundamental reference point for measuring distance. Secondly, contiguity-based neighbors are defined as the relationships between polygons that are adjacent or contiguous to each other. This method identifies polygons as neighbors if they share a common boundary or vertex.

After defining neighborhoods, the next step is to determine spatial weights. These relationships are outlined by a spatial weight's matrix. At this stage, we will also generate a scatterplot to assess spatial grouping in the data. An early step in spatial analysis is to investigate the presence of spatial dependence among observations. The formal word for this concept is spatial autocorrelation. Figure 7 depicts three distinct types of spatial autocorrelations.

Figure 7. Different Types of Spatial Autocorrelation



Source: Boraks, A., Plunkett, G.M., Doro, T.M. et al. (2021)

Spatial autocorrelation is commonly assessed using Moran's I, which measures how neighboring features relate to one another in terms of size relative to the mean. Positive cross-products occur when neighboring values are consistently larger or smaller than the average. Conversely, negative cross-products happen when values on either side of the mean differ in size. A more significant deviation from the mean results in more pronounced cross-products. Moran's Index is positive when values tend to cluster spatially (high values near high, low near low), while negative values indicate low values, and vice versa surround high values. When cross-products are balanced, the index approaches zero. The index is standardized by variance, resulting in values ranging from -1.0 to +1.0. The null hypothesis posits no spatial correlation, with rejection indicated by a high-test p-value.

The average spatial autocorrelation across all observations may be biased by edge effects, where crucial spatial components are outside the study area. Direct identification of spatial clusters is challenging. Thus, we will employ local measures of spatial autocorrelation, such as Local Indicators of Spatial Association (LISA), to disaggregate global results to identify "hot spots" of similar values within a given spatial dataset. LISA is an extension of the Global Moran's I statistic. It is valuable for exploratory analysis as it can identify both spatial clusters, where observations are surrounded by similar values (hot spots), and spatial outliers, where dissimilar values surround observations. This capability is illustrated through LISA's quadrant plot, which categorizes observations based on spatial relationships. It enables the creation of a "cluster map" showing cluster membership and statistical significance, thereby enhancing exploratory analysis.

5.3 Spatial Autoregressive Model (SAR)

Aligned with the objectives of this study, the primary purpose of spatial econometric estimation is to measure the spatial impact. The Spatial Autoregressive Model (SAR), also known as the Spatial Lag Model, is a critical tool in spatial econometrics designed to capture the interdependencies between spatial units. As Anselin (2013) emphasizes, spatial econometric models typically address two primary spatial effects: spatial dependence and spatial heterogeneity. Spatial dependence refers to the phenomenon where the value observed in one location depends on values observed in nearby locations. For example, in a study of tourism performance, an increase in one province's tourism activities could influence neighboring provinces due to shared resources and tourist flows. This relationship is captured mathematically in the SAR model by incorporating a spatially lagged dependent variable, which is essentially a weighted average of neighboring values, into the regression equation. The basic SAR model is represented as $y = \rho W y + X\beta + \epsilon$, where y is the dependent variable, W is the spatial weights matrix, ρ is the spatial autoregressive coefficient, X represents the explanatory variables, β is the coefficient vector, and ϵ is the error term (Anselin, 2013).

Additionally, spatial heterogeneity accounts for variations in relationships across different regions due to differing local characteristics. For instance, regions like Java and Bali might exhibit higher tourism workforce absorption due to better infrastructure compared to other regions (Elhorst, 2009). The SAR model effectively captures these spatial dynamics by explaining the variability of the dependent variable not just through traditional explanatory variables but also through spatially correlated observations, thereby providing a more nuanced understanding of spatial processes.

In practice, the estimation of the SAR model involves understanding both direct and indirect spatial effects. Direct effects pertain to the impact of changes in an explanatory variable within a specific location, while indirect effects (spillover effects) refer to the influence of these changes on neighboring locations. These effects are crucial for understanding the overall spatial interaction structure within the data, as articulated by LeSage and Fischer (2008), and are obtained through the spatial weighting matrix which quantifies the spatial relationships between different observational units.

For this study, we specify SAR model where the GRDP and unemployment are the dependent variables, the number of domestic tourists, the number of foreign tourists are the independent variables, and HDI, FDI, DDI, accommodation, and population density are the control variables. All variables, except for HDI, are expressed in logarithmic form. The following equation can represent the model:

Model 1:

$$\begin{aligned} ln(grdp)_i = {} & \rho_1 \Sigma_{j \neq i} W_{ij} ln(grdp)_j + \beta_1 ln(domestic\_tourist)_i + \beta_2 ln(foreign\_tourist)_i + \gamma_1 hdi_i \\ & + \gamma_2 ln(accommodation)_i + \gamma_3 ln(fdi)_i + \gamma_4 ln(ddi)_i + \gamma_5 ln(pop\_density)_i + \varepsilon_i \end{aligned}$$

Model 2:

$$\begin{aligned} & ln(unemployment)_i \\ & \quad = \rho_1 \Sigma_{j \neq i} W_{ij} ln(unemployment)_j + \beta_1 ln(domestic\_tourist)_i \\ & \quad + \beta_2 ln(foreign\_tourist)_i + \gamma_1 hdi_i + \gamma_2 ln(accommodation)_i + \gamma_3 ln(fdi)_i \\ & \quad + \gamma_4 ln(ddi)_i + \gamma_5 ln(pop\_density)_i + \varepsilon_i \end{aligned}$$

This model captures the direct impact of the independent and control variables on GRDP while accounting for spatial dependence through the spatially lagged dependent variable term $\rho \Sigma_j W_{ij} ln(grdp)_j$ and $\rho \Sigma_j W_{ij} ln(unemployment)_j$. The spatial weights matrix W reflects the spatial relationships between different regions, ensuring that the influence of neighboring regions' GRDP is incorporated into the model.

6. EMPIRICAL RESULT

6.1. Fixed Effect Regression Result

Table 2. Panel fixed effect model with ***GRDP*** *as the dependent variable*

GRDP	Fixed-effects estimates
	Coef.
Domestic Tourist	0.005 (0.004)
Foreign Tourist	0.008** (0.003)
Human Development	0.092*** (0.011)
Accommodation	0.076*** (0.034)
Foreign direct investment	0.014* (0.005)
Domestic direct investment	-0.009 (0.006)
Population Density	-0.840*** (0.079)
R-squared	0.7917
F-statistics	33.1209 ***
Number of obs	102
Number of groups	34

Note(s): **** P<0.001, ** P<0.01, * P<0.05*
Robust standard errors are in parentheses
Source(s): *Authors' estimates*

According to the first model of fixed effect regression result, the analyses underscore that tourism development, which is proxied by the number of domestic and foreign tourists' support for tourism's impact on GRDP. More specifically, this results reveals foreign tourism has a statistically significant positive impact on GRD. Unfortunately, domestic tourism does not have a statistically significant positive impact on GRDP in Indonesian provinces. These findings support that foreign tourists are crucial in increasing the GRDP. Moreover, these results align with the statement by Blanchard & Katz (1992): International tourists can boost economic growth through higher spending, while domestic tourism may have less impact due to lower spending or inadequate infrastructure. Additionally, these findings align with previous research in the literature review, including studies by Sinclair (1998), Croes and Vanegas (2008), and Song *et al.* (2012).

*Table 3. Panel fixed effect model with **Unemployment** as the dependent variable*

Unemployment	*Fixed-effects estimates*
	Coef.
Domestic Tourist	-0.033 (0.022)
Foreign Tourist	-0.090*** (0.025)
Human Development	0.107* (0.052)
Accommodation	-0.013 (0.033)
Foreign direct investment	-0.045 (0.033)
Domestic direct investment	0.011 (0.025)
Population Density	-1.001* (0.457)
R-squared	0.48406
F-statistics	8.17597 ***
Number of obs	102
Number of groups	34

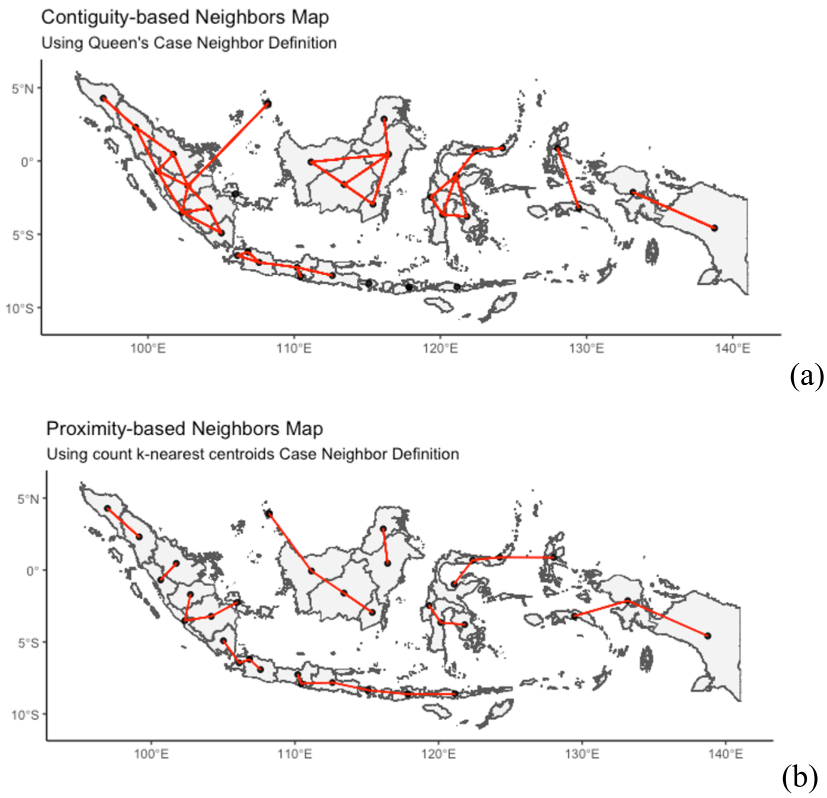
***Note(s):** *** P<0.001, ** P<0.01, * P<0.05*
Robust standard errors are in parentheses
***Source(s):** Authors' estimates*

According to the second model of fixed effect regression results, the analyses underscore that tourism development, proxied by both foreign and domestic tourism, has a complex impact on unemployment. Specifically, these results reveal foreign tourists have a statistically significant negative impact on unemployment, indicating that increased foreign tourists are associated with decreased unemployment rates. However, domestic tourism does not have a statistically significant impact on unemployment in Indonesian provinces. The findings suggest that foreign tourism plays a crucial role in reducing unemployment. This is aligned with Sinclair (1998), Croes and Vanegas (2008), and Loría *et al.* (2017) findings that increasing the number of international visitors significantly reduces the unemployment rate. Moreover, the economic activities generated by international tourism, which include higher spending on services and goods, tend to create more job opportunities in both the formal and informal sectors than domestic tourism. This is because international tourists' expenditures have a more substantial multiplier effect on the local economy (UNWTO, 2019).

6.2 Spatial Autocorrelation Result

In order to do spatial autocorrelation analysis, firstly, we will use a neighborhood definition that is determined by the contiguity of a queen's instance, as depicted in Figure 8a. Neighbors can also be categorized based on their closeness. Furthermore, not all regions are contiguous due to Indonesia's archipelagic nature. Thus, we selected a neighborhood definition based on the k-nearest proximity. Utilizing the k-nearest neighbors approach enhances the study by incorporating a broader range of data points and accurately representing spatial relationships, as depicted in Figure 8b. Neighborhood relationships can be visually represented via plotting functionality, wherein lines are formed to connect each polygon with its nearby polygons.

Figure 8. Spatial Neighborhoods



Source: Authors' result

Once neighborhoods are defined, determining spatial weights for each is essential. First, we will execute our Gross Regional Domestic Product (GRDP) model. Figure 9a shows that row index 1 has three neighbors, and each region is assigned a uniform weight of 0.333. The spatial weight matrix that was previously calculated assesses the spatial interdependence between observations. Subsequently, a scatterplot is generated to conduct an initial assessment of geographic clustering within the dataset, as depicted in Figure 9b. The plot illustrates a clear correlation between GRDP and its spatial lag, also known as the Moran scatter plot. To analyze this link, one might use a global spatial autocorrelation test.

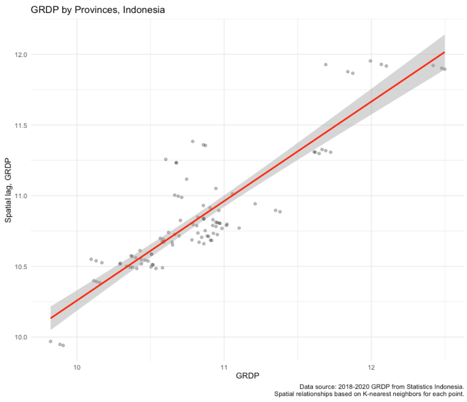
Figure 9. Global Spatial Autocorrelation - 1st Model (GRDP)

```
> weights <- nb2listw(idn.knn, style = "W")
> weights$weights[[1]]
[1] 0.3333333 0.3333333 0.3333333
> FinalData$lag_GRDP <- lag.listw(weights , FinalData$log_GRDP)

        Moran I test under randomisation

data:  FinalData$lag_GRDP
weights: weights

Moran I statistic standard deviate = 12.684, p-value < 2.2e-16
alternative hypothesis: greater
sample estimates:
Moran I statistic       Expectation          Variance
      0.919357188      -0.009900990       0.005367417
```



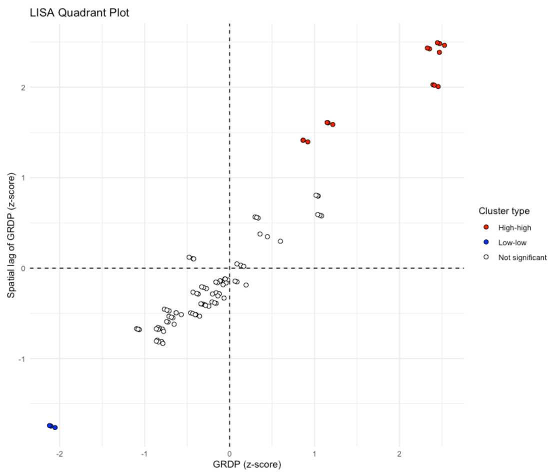
(a) Spatial weights and Global Moran's (b) Moran Scatter Plot

Source: Authors' result

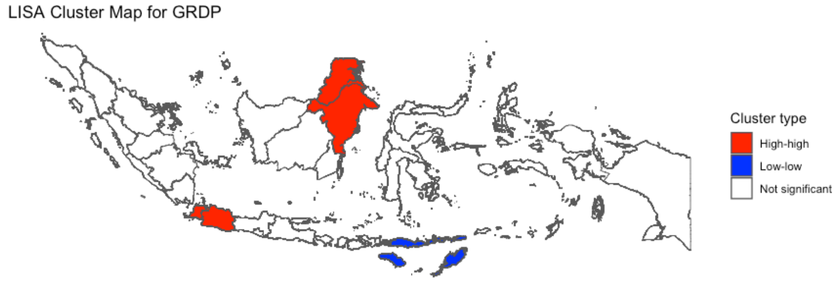
The Moran's I statistic of 0.9193 is positive, which suggests that the sample is spatially clustered, i.e., there is positive spatial autocorrelation. This means that provinces with higher GRDPs tend to be located near one another, and provinces with lower GRDPs tend to be found in the same areas. Subsequently, LISA will be employed to explore clustering and detect potential spatial outliers concerning GRDP in Indonesia.

Figure 10. Local Spatial Autocorrelation - (GRDP)

(a) LISA quadrant plot



(b) LISA Cluster MAP



Source: Authors' result

Based on Figure 10a, Observations falling in the top-right quadrant represent "high-high" clusters, where provinces with higher GRDP also surround provinces with higher GRDP. The bottom-left quadrant represents spatial clusters but instead includes provinces with lower GRDP that are also surrounded by provinces with lower GRDP. After identifying spatial clusters and finding no outliers. Then, we can plot a "cluster map" where observations are visualized in relationship to their cluster membership and statistical significance, as indicated by Figure 10b.

4.3.2. Spatial Data Analysis Result (Unemployment)

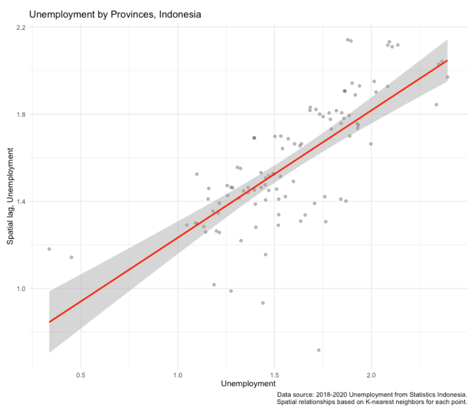
Figure 11. Global Spatial Autocorrelation - (Unemployment)

```
> weights2 <- nb2listw(idn.knn, style = "W")
> weights2$weights [[1]]
[1] 0.3333333 0.3333333 0.3333333
> FinalData$lag_unemployment <- lag.listw(weights2 , FinalData$log_unemployment)
> moran.test(FinalData$lag_unemployment, weights2)

        Moran I test under randomisation

data:  FinalData$lag_unemployment
weights: weights2

Moran I statistic standard deviate = 12.163, p-value < 2.2e-16
alternative hypothesis: greater
sample estimates:
Moran I statistic       Expectation          Variance
      0.886558235      -0.009900990       0.005431919
```



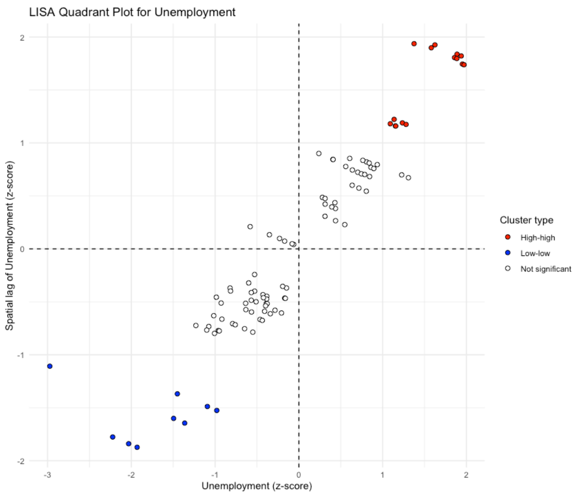
(a) Spatial weights and Global Moran's (b) Moran Scatter Plot

Source: Authors' result

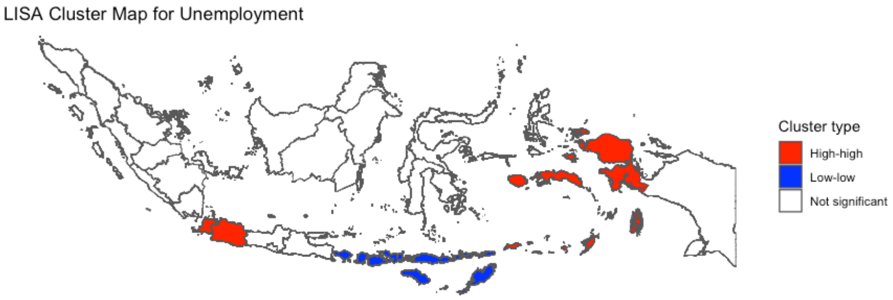
Based on Figure 11a shows that row index 1 has three neighbors, and each region is assigned a uniform weight of 0.333, and Moran's I statistic of 0.8665 is positive, which suggests that the sample is spatially clustered; i.e., positive spatial autocorrelation. This means that provinces with higher unemployment tend to be located near one another, and provinces with lower unemployment tend to be found in the same areas. Moreover, The scatterplot, denoted by 11b, suggests a positive correlation between Unemployment and its spatial lag. Next, LISA will be employed to explore clustering and detect potential spatial outliers concerning Unemployment in Indonesia.

Figure 12. Local Spatial Autocorrelation - (Unemployment)

(a) LISA quadrant plot



(b) LISA Cluster MAP



Source: Authors' result

Based on Figure 12a, Observations falling in the top-right quadrant represent "high-high" clusters, where provinces with higher Unemployment also surround provinces with higher Unemployment. The bottom-left quadrant represents spatial clusters but instead includes provinces with lower Unemployment that is also surrounded by provinces with lower Unemployment. After identifying spatial clusters and finding no outliers, we may create a "cluster map" showing observations by cluster membership and statistical significance, denoted by Figure 12b.

6.3 Spatial Autoregressive Model (SAR) Result

In order to analyze the dynamics of GRDP across different regions and over time, this study conducts separate SAR model estimations for each year from 2018 to 2020. This annual approach allows for the identification of temporal variations in the spatial relationships and the impact of independent variables on GRDP. By examining each year individually, it is possible to capture year-specific spatial dependencies and economic conditions that may influence the results. This method provides a detailed temporal and spatial understanding of the factors affecting GRDP, enhancing the robustness and specificity of the findings.

*Table 4. SAR model estimation with **GRDP** as the dependent variable for 2018, 2019, and 2020*

Variable	Coef. 2018	Coef. 2019	Coef. 2020
(Intercept)	3.4126 (2.1768070)	5.753586* (2.828206)	5.2936536** (1.9395250)
log_domestic_tourist	-0.1597 (0.1313419)	-0.209647 (0.136992)	-0.2292842* (0.0903079)
log_foreign_tourist	0.0446 (0.0334991)	0.047239 (0.034646)	0.0166737 (0.0344623)
hdi	0.0954*** (2.1768070)	0.078871** (0.025916)	0.0729664*** (1.9395250)
log_fdi	0.2363*** (0.0523910)	0.127347* (0.053697)	0.0076066 (0.0499975)
log_ddi	-0.0223 (0.0655314)	0.127222 (0.104011)	0.3107698** (0.1028217)
log_accommodation	0.0031 (0.0897974)	0.083265 (0.103582)	-0.0201964 (0.1019536)
log_pop_density	-0.1465* (0.0725917)	-0.186156** (0.068897)	-0.0228862 (0.0864335)
Spatial lag (ρ)	0.19919	0.10804	0.10535
Number of obs	34	34	34
R-squared	0.6043242	0.549103	0.5994905
Wald statistics	2.4168	0.65534	0.67086
Wald statistics p-value	0.12004	0.41821	0.41275

Note(s): **** P<0.001, ** P<0.01, * P<0.05*
Robust standard errors are in parentheses
Source(s): *Authors' estimates*

The SAR model results for 2018 indicated significant positive impacts of HDI and FDI on GRDP, underscoring the importance of human capital and foreign investments in regional economic performance. However, neither domestic tourists nor foreign tourists showed significant effects. Additionally, the non-significant spatial lag coefficient suggested limited inter-provincial spillover effects.

In 2019, HDI and FDI continued to positively impact GRDP, while domestic and foreign tourist variables remained non-significant. The persistent non-significance of the spatial lag coefficient indicated no spatial spillover effects between provinces.

By 2020, HDI and DDI significantly influenced GRDP. Interestingly, domestic tourists had a negative impact on GRDP, potentially due to challenges such as over-tourism or inadequate infrastructure, leading to economic inefficiencies (Ashley *et al*., 2007). Foreign tourists remained non-significant in their impact. Similarly, the spatial lag coefficient remained non-significant, indicating no observed spillover effects across provinces.

These results suggest that while human capital and investments are crucial for regional economic performance, the direct effects of domestic and foreign tourists on GRDP varied across the study period. The non-significant spatial lag coefficients indicate that economic activities are largely contained within provinces without significant regional spillover effects. Thus, in conclusion, this study highlights the complexity of tourism's economic impacts in Indonesia. The empirical findings suggest that domestic and foreign tourist numbers do not always translate into economic performance, and spatial spillover effects are minimal. This emphasizes the need for targeted policies that address infrastructure and sustainable tourism practices to fully influence tourism's potential for regional development (Ritchie & Crouch, 2003; Sinclair 1998).

Table 5. SAR model estimation with ***unemployment*** *as the dependent variable for 2018, 2019, and 2020*

Variable	Coef. 2018	Coef. 2019	Coef. 2020
(Intercept)	-1.81744324 (1.96613225)	-1.452902 (2.190024)	1.02840405 (1.03333985)
log_domestic_tourist	0.13280666 (0.12290064)	0.100752 (0.113261)	-0.10918924 (0.05594184)
log_foreign_tourist	-0.01840987 (0.03203438)	-0.016045 (0.028556)	-0.00096277 (0.02111175)
hdi	0.02968263 (0.01976032)	0.029763 (0.021151)	0.01294921 (1.03333985)
log_fdi	0.04597098 (0.05004302)	0.074245 (0.044412)	0.02060408 (0.03065074)
log_ddi	0.00018244 (0.06284947)	-0.065349 (0.085366)	0.08639546 (0.06313650)
log_accommodation	-0.06840725 (0.08400809)	-0.004075 (0.083899)	0.10748032 (0.06266375)
log_pop_density	-0.05327651 (0.06816837)	-0.047848 (0.056842)	0.05788696 (0.05296409)
Spatial lag (ρ)	-0.24019	-0.17275	-0.069468
Number of obs	34	34	34
R-squared	0.168017	0.1664465	0.5219686

Wald statistics	2.4191	1.2074	0.23772
Wald statistics p-value	0.11987	0.27184	0.62586

Note(s): **** P<0.001, ** P<0.01, * P<0.05*
Robust standard errors are in parentheses
Source(s): *Authors' estimates*

The SAR model results for unemployment across Indonesian provinces from 2018 to 2020 reveal that tourism-related variables generally do not significantly impact unemployment rates statistically. In 2018, none of the variables demonstrate significant relationships with unemployment. This trend persists into 2019, where both tourism-related variables and other economic factors fail to significantly influence unemployment.

However, in 2020, the results slightly differ with accommodation showing an "almost" significant positive relationship, suggesting that increased accommodation capacity might correlate with higher unemployment. This counterintuitive finding might indicate that expanding accommodation facilities does not directly immediately make job creation, which could lead to inefficiencies and temporary job losses. The number of domestic tourists also shows a near-significant negative relationship, indicating a potential reduction in unemployment with an increase in the number of domestic tourists.

These results partially reject the hypothesis that the number of domestic and foreign tourists significantly reduces unemployment rates. The previous researches suggest that tourism should create jobs and reduce unemployment (Sinclair, 1998; Brida *et al.*, 2018). However, these findings show that the impact of tourism on unemployment is not straightforward and can depend on various factors. The influence of tourism may vary based on the specific economic conditions of a region, how efficiently the local economy operates, or the nature of the jobs generated by the tourism industry. This means that while tourism has the potential to reduce unemployment, its effectiveness can be limited by local circumstances.

7. CONCLUSION

This study concludes that tourism development, particularly international tourism, plays a significant role in influencing economic performance and reducing unemployment in Indonesian provinces. The fixed effect regression analysis indicates that foreign tourism has a statistically significant positive impact on GRDP, highlighting its importance in boosting economic activities. In contrast, domestic tourism does not show a significant effect on GRDP. Additionally, foreign tourism is found to significantly reduce unemployment rates, while domestic tourism does not have a notable impact on employment levels. The spatial analysis indicates that economic activities and unemployment rates demonstrate spatial clustering. Additionally, there is a positive spatial autocorrelation between Gross Regional Domestic Product (GRDP) and unemployment, suggesting that regions with higher GRDP or lower unemployment tend to be geographically close to each other. However, the study observes limited regional spillover effects, implying that economic benefits are mostly confined within individual provinces or regions.

These findings underscore the need for targeted policies that enhance infrastructure and promote sustainable tourism practices to maximize tourism's potential for regional development. Unlike domestic tourism, the study highlights that foreign tourism significantly contributes to economic growth and reduces unemployment. This disparity suggests that infrastructure and service quality, crucial for attracting and retaining international tourists, may be inadequate to fully leverage the potential of domestic tourism. Policymakers should focus on attracting more international tourists through targeted marketing campaigns, simplified visa procedures, and investment in tourism infrastructure. Simultaneously, creating travel incentives, improving infrastructure, and promoting local attractions are key for boosting domestic tourism. Investing in education and healthcare will enhance workforce productivity and overall economic growth. Encouraging foreign direct investment through incentives and public-private partnerships can further develop tourism. Additionally, better urban planning and promoting rural tourism can mitigate the negative effects of high population density. These strategies aim to maximize the economic benefits of both foreign and domestic tourism, fostering sustainable and inclusive growth.

Appendix - R Prompts

```
setwd("/Users/ignatiusharry/Library/CloudStorage/Dropbox/Data/S2/NCCU/2nd Semester/Local Public Finance/2nd Assignment (Presentation)/Data")
```

Figure A: VIF-Model 1

```
> # Model 1 ------------------------------------------------------------------
>
> # Multicollinearity Test
> # Fit OLS model directly
> ols_model <- lm(log_GRDP ~ log_domestic_tourist + log_foreign_tourist + log_tourism_employment +HDI + log_accommodation + log_FDI + log_DDI + log_pop_
density, data = FinalData)
> # Calculate VIF
> library(car)
> vif(ols_model)
  log_domestic_tourist    log_foreign_tourist log_tourism_employment                    HDI
              4.373737               1.455726              12.181776               2.392064
     log_accommodation                log_FDI                log_DDI        log_pop_density
              4.756030               1.746594               3.202520               3.608770
> #All VIF values are below 10, except log_tourism employment. thus we exclude log tourism employment in our model
```

Note: Tourist employment was omitted due to multicollinearity.

Figure B: Normality, Homoscedasticity, and Autocorrelation of Residual Tests - Model 1

```
> # Classical Assumption Tests
> # Normality Test of Residuals
> shapiro.test(model_grdp$residuals)

	Shapiro-Wilk normality test

data:  model_grdp$residuals
W = 0.98267, p-value = 0.2026

> #Result: P>0.05 = reject h0 (Residual is normal distribution (GOOD))
>
> # Homoscedasticity Test
> library(lmtest)
> bptest(model_grdp, studentize = FALSE, data =pdata)

	Breusch-Pagan test

data:  model_grdp
BP = 21.709, df = 7, p-value = 0.002851

> #Result: P < 0.05 = Reject H0 (This indicates evidence of heteroscedasticity, meaning that the variance of residuals is not constant across observation
s.)
>
> # Autocorrelation of Residuals
> # Wooldridge test for autocorrelation in panel data
> wooldridge_test <- pwartest(model_grdp)
> print(wooldridge_test)

	Wooldridge's test for serial correlation in FE panels

data:  model_grdp
F = 1.7279, df1 = 1, df2 = 66, p-value = 0.1932
alternative hypothesis: serial correlation

> #Result: P>0.05 = Fail to reject H0 (No significant evidence of serial correlation in the residuals.)
```

Figure C: Fixed effect Regression - Model 1

```
> model_grdp  <- plm(formula = log_GRDP ~ log_domestic_tourist + log_foreign_tourist + HDI + log_accommodation + log_FDI + log_DDI + log_pop_density, model
= "within", data = pdata)
> summary(model_grdp)
Oneway (individual) effect Within Model

Call:
plm(formula = log_GRDP ~ log_domestic_tourist + log_foreign_tourist +
    HDI + log_accommodation + log_FDI + log_DDI + log_pop_density,
    data = pdata, model = "within")

Balanced Panel: n = 34, T = 3, N = 102

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-0.05644790 -0.01231686  0.00016733  0.01286367  0.06262872

Coefficients:
                       Estimate Std. Error t-value  Pr(>|t|)
log_domestic_tourist  0.0050807  0.0050816  0.9998   0.32134
log_foreign_tourist   0.0084713  0.0037025  2.2880   0.02562 *
HDI                   0.0922581  0.0106870  8.6327 3.613e-12 ***
log_accommodation     0.0757085  0.0137627  5.5010 7.909e-07 ***
log_FDI               0.0135283  0.0054580  2.4786   0.01597 *
log_DDI              -0.0090769  0.0054978 -1.6510   0.10387
log_pop_density      -0.8395068  0.1000630 -8.3898 9.415e-12 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    0.20335
Residual Sum of Squares: 0.042359
R-Squared:      0.7917
Adj. R-Squared: 0.65511
F-statistic: 33.1209 on 7 and 61 DF, p-value: < 2.22e-16
```

Figure D: Fixed effect Regression with Robustness Test - Model 1

```
> # Calculate robust standard errors
> robust_se <- vcovHC(model_grdp, type = "HC4")
>
> # Use coeftest to get robust standard errors
> robust_summary <- coeftest(model_grdp, vcov = robust_se)
>
> # Print the robust summary
> print(robust_summary)

t test of coefficients:

                       Estimate Std. Error  t value  Pr(>|t|)
log_domestic_tourist  0.0050807  0.0042553   1.1940  0.237108
log_foreign_tourist   0.0084713  0.0029025   2.9187  0.004918 **
HDI                   0.0922581  0.0113929   8.0979 2.985e-11 ***
log_accommodation     0.0757085  0.0338227   2.2384  0.028856 *
log_FDI               0.0135283  0.0055298   2.4464  0.017325 *
log_DDI              -0.0090769  0.0062590  -1.4502  0.152123
log_pop_density      -0.8395068  0.0793607 -10.5784 1.986e-15 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Note: We chose HC4 because it is conservative, data-driven, and ideal for small samples or leverage concerns.

Figure E: VIF - Model 2

```
> # 2nd model ------------------------------------------------------------
> # Multicollinearity Test
> # Fit OLS model directly
> ols_model2 <- lm(log_unemployment ~ log_domestic_tourist + log_foreign_tourist + log_tourism_employment + HDI + log_accommodation + log_FDI + log_DDI + log_
pop_density, data = FinalData)
> # Calculate VIF
> library(car)
> vif(ols_model2)
  log_domestic_tourist    log_foreign_tourist log_tourism_employment                    HDI
              4.373737               1.455726              12.181776               2.392064
     log_accommodation                log_FDI                log_DDI        log_pop_density
              4.756030               1.746594               3.202520               3.608770
> #All VIF values are below 10, except log_tourism employment. thus we exclude log tourism employment in our model
```

Note: Tourist employment was omitted due to multicollinearity.

Figure F: Normality, Homoscedasticity, and Autocorrelation of Residual Tests - Model 2

```
> # Classical Assumption Tests
> # Normality Test of Residuals
> shapiro.test(model_unemployment$residuals)

	Shapiro-Wilk normality test

data:  model_unemployment$residuals
W = 0.77556, p-value = 3.512e-11

> #Result: P>0.05 = reject h0 (Residual is normal distribution (GOOD))
>
> # Homoscedasticity Test
> library(lmtest)
> bptest(model_unemployment, studentize = FALSE, data =pdata)

	Breusch-Pagan test

data:  model_unemployment
BP = 54.517, df = 7, p-value = 1.858e-09

> #Result: P < 0.05 = Reject H0 (This indicates evidence of heteroscedasticity, meaning that the variance of residuals is not constant across observations.)
>
> # Autocorrelation of Residuals
> # Wooldridge test for autocorrelation in panel data
> wooldridge_test <- pwartest(model_unemployment)
> print(wooldridge_test)

	Wooldridge's test for serial correlation in FE panels

data:  model_unemployment
F = 0.31466, df1 = 1, df2 = 66, p-value = 0.5767
alternative hypothesis: serial correlation

> #Result: P>0.05 = Fail to reject H0 (No significant evidence of serial correlation in the residuals.)
```

Figure G: Fixed effect Regression - Model 2

```
> model_unemployment  <- plm(formula = log_unemployment ~ log_domestic_tourist + log_foreign_tourist + HDI + log_accommodation + log_FDI + log_DDI + log_pop_den
sity, model = "within", data = pdata)
> summary(model_unemployment)
Oneway (individual) effect Within Model

Call:
plm(formula = log_unemployment ~ log_domestic_tourist + log_foreign_tourist +
    HDI + log_accommodation + log_FDI + log_DDI + log_pop_density,
    data = pdata, model = "within")

Balanced Panel: n = 34, T = 3, N = 102

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-0.38377675 -0.05306150  0.00087787  0.04629285  0.74386338

Coefficients:
                      Estimate Std. Error t-value  Pr(>|t|)
log_domestic_tourist -0.032736   0.028536 -1.1472   0.25579
log_foreign_tourist  -0.090018   0.020791 -4.3296 5.653e-05 ***
HDI                   0.107418   0.060013  1.7899   0.07843 .
log_accommodation    -0.012516   0.077285 -0.1619   0.87188
log_FDI              -0.045435   0.030649 -1.4824   0.14337
log_DDI               0.010538   0.030873  0.3413   0.73403
log_pop_density      -1.000500   0.561905 -1.7805   0.07997 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    2.589
Residual Sum of Squares: 1.3357
R-Squared:      0.48406
Adj. R-Squared: 0.14575
F-statistic: 8.17597 on 7 and 61 DF, p-value: 5.4063e-07
```

Figure H: Fixed effect Regression with robustness test - Model 2

```
> # Calculate robust standard errors
> robust_se2 <- vcovHC(model_unemployment, type = "HC4")
>
> # Use coeftest to get robust standard errors
> robust_summary2 <- coeftest(model_unemployment, vcov = robust_se2)
>
> # Print the robust summary
> print(robust_summary2)

t test of coefficients:

                     Estimate Std. Error t value  Pr(>|t|)
log_domestic_tourist -0.032736   0.022216 -1.4735 0.1457625
log_foreign_tourist  -0.090018   0.024738 -3.6388 0.0005653 ***
HDI                   0.107418   0.051538  2.0842 0.0413327 *
log_accommodation    -0.012516   0.033117 -0.3779 0.7067873
log_FDI              -0.045435   0.033040 -1.3752 0.1741138
log_DDI               0.010538   0.025397  0.4149 0.6796564
log_pop_density      -1.000500   0.456997 -2.1893 0.0324117 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Note: We chose HC4 because it is conservative, data-driven, and ideal for small samples or leverage concerns.

Figure I: Spatial Autoregressive Model - Model 1 (2018)

```
> slm_grdp_2018 <- lagsarlm(log_grdp ~ log_domestic_tourist + log_foreign_tourist + HDI + log_FDI + log_DDI + log_accommodation + log_pop_density,
data = pdata_cross_2018, listw = lw)
>
> # Print summary - Model 1 (2018)
> print(summary(slm_grdp_2018))

Call:lagsarlm(formula = log_grdp ~ log_domestic_tourist + log_foreign_tourist +     HDI + log_FDI + log_DDI + log_accommodation + log_pop_density,
    data = pdata_cross_2018, listw = lw)

Residuals:
      Min        1Q    Median        3Q       Max
-0.573765 -0.238540 -0.073532  0.317548  0.900484

Type: lag
Coefficients: (asymptotic standard errors)
                      Estimate Std. Error z value  Pr(>|z|)
(Intercept)           3.4126487  2.1768070  1.5677   0.11694
log_domestic_tourist -0.1597325  0.1313419 -1.2162   0.22392
log_foreign_tourist   0.0445942  0.0334991  1.3312   0.18312
HDI                   0.0953948  0.0214631  4.4446 8.805e-06
log_FDI               0.2363337  0.0523910  4.5110 6.453e-06
log_DDI              -0.0222733  0.0655314 -0.3399   0.73394
log_accommodation     0.0031003  0.0897974  0.0345   0.97246
log_pop_density      -0.1464995  0.0725917 -2.0181   0.04358

Rho: 0.19919, LR test value: 1.3718, p-value: 0.24151
Asymptotic standard error: 0.12813
    z-value: 1.5546, p-value: 0.12004
Wald statistic: 2.4168, p-value: 0.12004

Log likelihood: -11.92987 for lag model
ML residual variance (sigma squared): 0.11582, (sigma: 0.34033)
Number of observations: 34
Number of parameters estimated: 10
AIC: 43.86, (AIC for lm: 43.232)
LM test for residual autocorrelation
test value: 1.8663, p-value: 0.1719
```

Figure J: Spatial Autoregressive Model - R-squared Model 1 (2018)

```
> # Fit the null model (only intercept)
> null_model <- lagsarlm(log_grdp ~ 1, data = pdata_cross_2018, listw = lw)
>
> # Extract log-likelihoods
> logLik_full <- logLik(slm_grdp_2018)
> logLik_null <- logLik(null_model)
>
> # Calculate the R-squared for Model 1 (2018)
> n <- length(log_grdp)
> pseudo_r_squared <- 1 - (exp(logLik_null - logLik_full))^(2/n)
> pseudo_r_squared <- as.numeric(pseudo_r_squared)
>
> print(pseudo_r_squared)
[1] 0.6043242
```

Figure K: Spatial Autoregressive Model - Model 2 (2018)

```
> slm_unemployment_2018 <- lagsarlm(log_unemployment ~ log_domestic_tourist + log_foreign_tourist + HDI + log_FDI + log_DDI + log_accommodation +
log_pop_density, data = pdata_cross_2018, listw = lw)
>
> # Print summary - Model 2 (2018)
> print(summary(slm_unemployment_2018))

Call:lagsarlm(formula = log_unemployment ~ log_domestic_tourist +     log_foreign_tourist + HDI + log_FDI + log_DDI + log_accommodation +
    log_pop_density, data = pdata_cross_2018, listw = lw)

Residuals:
      Min        1Q    Median        3Q       Max
-0.959262 -0.210221 -0.030918  0.138940  0.670666

Type: lag
Coefficients: (asymptotic standard errors)
                        Estimate  Std. Error z value Pr(>|z|)
(Intercept)          -1.81744324  1.96613225 -0.9244   0.3553
log_domestic_tourist  0.13280666  0.12290064  1.0806   0.2799
log_foreign_tourist  -0.01840987  0.03203438 -0.5747   0.5655
HDI                   0.02968263  0.01976032  1.5021   0.1331
log_FDI               0.04597098  0.05004302  0.9186   0.3583
log_DDI               0.00018244  0.06284947  0.0029   0.9977
log_accommodation    -0.06840725  0.08400809 -0.8143   0.4155
log_pop_density      -0.05327651  0.06816837 -0.7815   0.4345

Rho: -0.24019, LR test value: 2.3646, p-value: 0.12411
Asymptotic standard error: 0.15443
    z-value: -1.5553, p-value: 0.11987
Wald statistic: 2.4191, p-value: 0.11987

Log likelihood: -10.54353 for lag model
ML residual variance (sigma squared): 0.10588, (sigma: 0.32539)
Number of observations: 34
Number of parameters estimated: 10
AIC: 41.087, (AIC for lm: 41.452)
LM test for residual autocorrelation
test value: 0.022551, p-value: 0.88063
```

Figure L: Spatial Autoregressive Model - R-squared Model 2 (2018)

```
> # Fit the null model (only intercept)
> null_model <- lagsarlm(log_unemployment ~ 1, data = pdata_cross_2018, listw = lw)
>
> # Extract log-likelihoods
> logLik_full <- logLik(slm_unemployment_2018)
> logLik_null <- logLik(null_model)
>
> # Calculate the R-squared for Model 2 (2018)
> n <- length(log_unemployment)
> pseudo_r_squared <- 1 - (exp(logLik_null - logLik_full))^(2/n)
> pseudo_r_squared <- as.numeric(pseudo_r_squared)
>
> print(pseudo_r_squared)
[1] 0.168017
```

Figure M: Spatial Autoregressive Model - Model 1 (2019)

```
> slm_grdp_2019 <- lagsarlm(log_grdp ~ log_domestic_tourist + log_foreign_tourist + HDI + log_FDI + log_DDI + log_accommodation + log_pop_density,
data = pdata_cross_2019, listw = lw)
>
> # Print summary - Model 1 (2019)
> print(summary(slm_grdp_2019))

Call:lagsarlm(formula = log_grdp ~ log_domestic_tourist + log_foreign_tourist +
    HDI + log_FDI + log_DDI + log_accommodation + log_pop_density,     data = pdata_cross_2019, listw = lw)

Residuals:
      Min        1Q    Median        3Q       Max
-0.435648 -0.270747 -0.071889  0.253567  1.108319

Type: lag
Coefficients: (asymptotic standard errors)
                      Estimate Std. Error z value Pr(>|z|)
(Intercept)           5.753586   2.828206  2.0344 0.041915
log_domestic_tourist -0.209647   0.136992 -1.5304 0.125927
log_foreign_tourist   0.047239   0.034646  1.3635 0.172738
HDI                   0.078871   0.025916  3.0434 0.002339
log_FDI               0.127347   0.053697  2.3716 0.017711
log_DDI               0.127222   0.104011  1.2232 0.221270
log_accommodation     0.083265   0.103582  0.8039 0.421478
log_pop_density      -0.186156   0.068897 -2.7019 0.006893

Rho: 0.10804, LR test value: 0.36382, p-value: 0.54639
Asymptotic standard error: 0.13346
    z-value: 0.80953, p-value: 0.41821
Wald statistic: 0.65534, p-value: 0.41821

Log likelihood: -13.86914 for lag model
ML residual variance (sigma squared): 0.13164, (sigma: 0.36282)
Number of observations: 34
Number of parameters estimated: 10
AIC: 47.738, (AIC for lm: 46.102)
LM test for residual autocorrelation
test value: 1.2433, p-value: 0.26484
```

Figure N: Spatial Autoregressive Model - R-squared Model 1 (2019)

```
> # Fit the null model (only intercept)
> null_model <- lagsarlm(log_grdp ~ 1, data = pdata_cross_2019, listw = lw)
>
> # Extract log-likelihoods
> logLik_full <- logLik(slm_grdp_2019)
> logLik_null <- logLik(null_model)
>
> # Calculate the R-squared for Model 1 (2019)
> n <- length(log_grdp)
> pseudo_r_squared <- 1 - (exp(logLik_null - logLik_full))^(2/n)
> pseudo_r_squared <- as.numeric(pseudo_r_squared)
>
> print(pseudo_r_squared)
[1] 0.549103
```

Figure O: Spatial Autoregressive Model - Model 2 (2019)

```
> slm_unemployment_2019 <- lagsarlm(log_unemployment ~ log_domestic_tourist + log_foreign_tourist + HDI + log_FDI + log_DDI + log_accommodation +
log_pop_density, data = pdata_cross_2019, listw = lw)
>
> # Print summary - Model 2 (2019)
> print(summary(slm_unemployment_2019))

Call:lagsarlm(formula = log_unemployment ~ log_domestic_tourist +     log_foreign_tourist + HDI + log_FDI + log_DDI + log_accommodation +
    log_pop_density, data = pdata_cross_2019, listw = lw)

Residuals:
      Min        1Q    Median        3Q       Max
-0.955940 -0.140704 -0.007553  0.115391  0.525490

Type: lag
Coefficients: (asymptotic standard errors)
                      Estimate Std. Error z value Pr(>|z|)
(Intercept)          -1.452902   2.190024 -0.6634  0.50706
log_domestic_tourist  0.100752   0.113261  0.8896  0.37371
log_foreign_tourist  -0.016045   0.028556 -0.5619  0.57421
HDI                   0.029763   0.021151  1.4072  0.15937
log_FDI               0.074245   0.044412  1.6717  0.09458
log_DDI              -0.065349   0.085366 -0.7655  0.44396
log_accommodation    -0.004075   0.083899 -0.0486  0.96126
log_pop_density      -0.047848   0.056842 -0.8418  0.39991

Rho: -0.17275, LR test value: 1.2314, p-value: 0.26714
Asymptotic standard error: 0.15721
    z-value: -1.0988, p-value: 0.27184
Wald statistic: 1.2074, p-value: 0.27184

Log likelihood: -7.56025 for lag model
ML residual variance (sigma squared): 0.090044, (sigma: 0.30007)
Number of observations: 34
Number of parameters estimated: 10
AIC: 35.121, (AIC for lm: 34.352)
LM test for residual autocorrelation
test value: 0.13885, p-value: 0.70943
```

Figure P: Spatial Autoregressive Model - R-squared Model 2 (2019)

```
> # Fit the null model (only intercept)
> null_model <- lagsarlm(log_unemployment ~ 1, data = pdata_cross_2019, listw = lw)
>
> # Extract log-likelihoods
> logLik_full <- logLik(slm_unemployment_2019)
> logLik_null <- logLik(null_model)
>
> # Calculate the R-squared for Model 2 (2019)
> n <- length(log_unemployment)
> pseudo_r_squared <- 1 - (exp(logLik_null - logLik_full))^(2/n)
> pseudo_r_squared <- as.numeric(pseudo_r_squared)
>
> print(pseudo_r_squared)
[1] 0.1664465
```

Figure Q: Spatial Autoregressive Model - Model 1 (2020)

```
> slm_grdp_2020 <- lagsarlm(log_grdp ~ log_domestic_tourist + log_foreign_tourist + HDI + log_FDI + log_DDI + log_accommodation + log_pop_density,
data = pdata_cross_2020, listw = lw)
>
> # Print summary - Model 1 (2020)
> print(summary(slm_grdp_2020))

Call:lagsarlm(formula = log_grdp ~ log_domestic_tourist + log_foreign_tourist +
    HDI + log_FDI + log_DDI + log_accommodation + log_pop_density,     data = pdata_cross_2020, listw = lw)

Residuals:
      Min        1Q    Median        3Q       Max
-0.622994 -0.136116 -0.013145  0.122785  0.948681

Type: lag
Coefficients: (asymptotic standard errors)
                       Estimate Std. Error z value  Pr(>|z|)
(Intercept)           5.2936536  1.9395250  2.7294 0.0063458
log_domestic_tourist -0.2292842  0.0903079 -2.5389 0.0111197
log_foreign_tourist   0.0166737  0.0344623  0.4838 0.6285111
HDI                   0.0729664  0.0218930  3.3329 0.0008596
log_FDI               0.0076066  0.0499975  0.1521 0.8790764
log_DDI               0.3107698  0.1028217  3.0224 0.0025077
log_accommodation    -0.0201964  0.1019536 -0.1981 0.8429713
log_pop_density      -0.0228862  0.0864335 -0.2648 0.7911759

Rho: 0.10535, LR test value: 0.37254, p-value: 0.54162
Asymptotic standard error: 0.12863
    z-value: 0.81906, p-value: 0.41275
Wald statistic: 0.67086, p-value: 0.41275

Log likelihood: -11.38595 for lag model
ML residual variance (sigma squared): 0.11378, (sigma: 0.33731)
Number of observations: 34
Number of parameters estimated: 10
AIC: 42.772, (AIC for lm: 41.144)
LM test for residual autocorrelation
test value: 0.10771, p-value: 0.74276
```

Figure R: Spatial Autoregressive Model - R-squared Model 1 (2020)

```
> # Fit the null model (only intercept)
> null_model <- lagsarlm(log_grdp ~ 1, data = pdata_cross_2020, listw = lw)
>
> # Extract log-likelihoods
> logLik_full <- logLik(slm_grdp_2020)
> logLik_null <- logLik(null_model)
>
> # Calculate the R-squared for Model 1 (2020)
> n <- length(log_grdp)
> pseudo_r_squared <- 1 - (exp(logLik_null - logLik_full))^(2/n)
> pseudo_r_squared <- as.numeric(pseudo_r_squared)
>
> print(pseudo_r_squared)
[1] 0.5994905
```

Figure S: Spatial Autoregressive Model - Model 2 (2020)

```
> slm_unemployment_2020 <- lagsarlm(log_unemployment ~ log_domestic_tourist + log_foreign_tourist + HDI + log_FDI + log_DDI + log_accommodation +
log_pop_density, data = pdata_cross_2020, listw = lw)
>
> # Print summary - Model 2 (2020)
> print(summary(slm_unemployment_2020))

Call:lagsarlm(formula = log_unemployment ~ log_domestic_tourist +     log_foreign_tourist + HDI + log_FDI + log_DDI + log_accommodation +
    log_pop_density, data = pdata_cross_2020, listw = lw)

Residuals:
      Min        1Q    Median        3Q       Max
-0.372512 -0.135530 -0.022663  0.065548  0.427454

Type: lag
Coefficients: (asymptotic standard errors)
                        Estimate  Std. Error z value Pr(>|z|)
(Intercept)           1.02840405  1.03333985  0.9952  0.31963
log_domestic_tourist -0.10918924  0.05594184 -1.9518  0.05096
log_foreign_tourist  -0.00096277  0.02111175 -0.0456  0.96363
HDI                   0.01294921  0.01293727  1.0009  0.31686
log_FDI               0.02060408  0.03065074  0.6722  0.50144
log_DDI               0.08639546  0.06313650  1.3684  0.17119
log_accommodation     0.10748032  0.06266375  1.7152  0.08631
log_pop_density       0.05788696  0.05296409  1.0929  0.27442

Rho: -0.069468, LR test value: 0.26234, p-value: 0.60852
Asymptotic standard error: 0.14248
    z-value: -0.48756, p-value: 0.62586
Wald statistic: 0.23772, p-value: 0.62586

Log likelihood: 5.337349 for lag model
ML residual variance (sigma squared): 0.042675, (sigma: 0.20658)
Number of observations: 34
Number of parameters estimated: 10
AIC: 9.3253, (AIC for lm: 7.5876)
LM test for residual autocorrelation
test value: 1.6233, p-value: 0.20263
```

Figure T: Spatial Autoregressive Model - R-squared Model 2 (2020)

```
> # Fit the null model (only intercept)
> null_model <- lagsarlm(log_unemployment ~ 1, data = pdata_cross_2020, listw = lw)
>
> # Extract log-likelihoods
> logLik_full <- logLik(slm_unemployment_2020)
> logLik_null <- logLik(null_model)
>
> # Calculate the R-squared for Model 2 (2020)
> n <- length(log_unemployment)
> pseudo_r_squared <- 1 - (exp(logLik_null - logLik_full))^(2/n)
> pseudo_r_squared <- as.numeric(pseudo_r_squared)
>
> print(pseudo_r_squared)
[1] 0.5219686
```

References

Anselin, L. (2013). Spatial econometrics: Methods and models. Kluwer Academic Publishers.

Ashley, C., De Brine, P., Lehr, A., & Wilde, H. (2007). The role of the tourism sector in expanding economic opportunity. Kennedy School of Government, Harvard University.

Blanchard, O. J., & Katz, L. F. (1992). Regional evolutions. Brookings Papers on Economic Activity, 1992(1), 1-75.

Boraks, A., Plunkett, G. M., Doro, T. M., et al. (2021). Scale-dependent influences of distance and vegetation on the composition of aboveground and belowground tropical fungal communities. Microbial Ecology, 81, 874-883. https://doi.org/10.1007/s00248-020-01608-4

Brida, J. G., Pereyra, J. S., & Such, D. (2018). Unemployment and international tourism: The case of Spanish provinces. Tourism Economics, 24(7), 817-833.

Brown, G., & Green, R. (2021). Spatial dependence and tourism-led regional development: Evidence from Indonesia. Tourism Economics, 27(1), 3-21.

Chen, J., Lam, T., & Hsu, C. H. C. (2016). Tourism economics: A new perspective. Routledge.

Croes, R., & Vanegas, M. (2008). Cointegration and causality between tourism and poverty reduction. Journal of Travel Research, 47(1), 94-103.

Croes, R., & Vanegas, M. (2008). Tourism as a catalyst for economic development: A comparative case study analysis. Tourism Economics, 14(4), 673-690.

Dwyer, L., Forsyth, P., & Dwyer, W. (2010). Tourism economics and policy. Channel View Publications.

Elhorst, J. P. (2009). Spatial panel data models. In M. Fischer & A. Getis (Eds.), Handbook of applied spatial analysis. Springer.

Fall, R. (2019). Tourism and economic inequality: The case of Indonesia. Tourism Economics, 25(2), 255-274.

Gursoy, D., Chi, C. G., Ai, J., & Chen, B. T. (2012). How does perceived value affect travelers' satisfaction and loyalty? Annals of Tourism Research, 39(2), 798-804.

Hampton, M. P., & Jeyacheya, J. (2015). Tourism and inclusive growth in small island developing states. Journal of International Development, 27(4), 549-565.

Kuncoro, M. (2004). Otonomi dan pembangunan daerah: Reformasi, perencanaan, strategi, dan peluang. Retrieved from https://nla.gov.au/nla.cat-vn3246681

LeSage, J. P., & Fischer, M. M. (2008). Spatial growth regressions: Model specification, estimation and interpretation. Spatial Economic Analysis.

Loría, E., Sánchez, F., & Salas, E. (2017). Efectos de la llegada de viajeros internacionales en el desempleo y el crecimiento económico en México, 2000.2-2015.2. El Periplo Sustentable, 32, 1-24.

Ministry of Tourism and Creative Economy. (2019). Tourism contributes 4.97% to Indonesia's GDP in 2019. Retrieved from https://www.indonesia.travel/gb/en/about/organization/ministry-of-tourism-and-creative-economy

OECD. (2020). Foreign direct investment statistics: Data, analysis and forecasts. Retrieved from https://www.oecd.org/investment/statistics.htm

Ritchie, J. R. B., & Crouch, G. I. (2003). The competitive destination: A sustainable tourism perspective. CABI.

Sinclair, M. T. (1998). Tourism and economic development: A survey. Journal of Development Studies, 34(5), 1-51.

Song, H., Witt, S. F., & Li, G. (2000). Tourism demand modelling and forecasting: Modern econometric approaches. Routledge.

Sugiyarto, G., Blake, A., & Sinclair, M. T. (2003). Tourism and economic development: A survey. The Annals of Regional Science, 37(1), 1-29.

Tang, C. F., & Tan, E. C. (2015). Does tourism effectively stimulate Malaysia's economic growth? Tourism Management, 46, 158-163.

Telfer, D. J., & Sharpley, R. (2008). Tourism and development in the developing world. Routledge.

Tobler, W. R. (1970). A computer movie simulating urban growth in the Detroit region. Economic Geography, 46(2), 234-240.

United Nations Development Programme. (2019). Human development report 2019. UNDP.

United Nations World Tourism Organization. (2013). Economic impact of tourism. UNWTO Tourism Highlights.

United Nations World Tourism Organization. (2019). International tourism highlights. UNWTO.

Wooldridge, J. M. (2010). Econometric analysis of cross section and panel data. MIT Press.

World Bank. (2020). Indonesia economic prospects: The long road to recovery.

World Bank. (2020). World development indicators. Retrieved from https://data.worldbank.org/indicator

Yeliz Mert Kantar, & Günay Aktaş, S. (2016). Spatial correlation analysis of unemployment rates in Turkey. Journal of Eastern Europe Research in Business and Economics, 2016(136996). https://doi.org/10.5171/2016.136996