



**Tourism Economics**

# **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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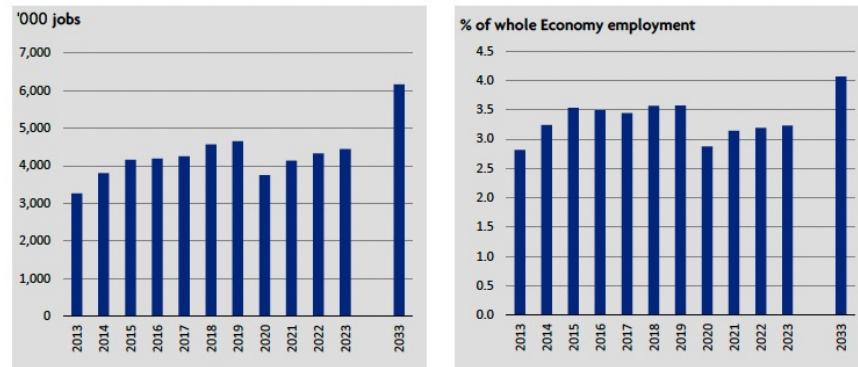
Marcella Alifia Kuswana Putri 潘怡璇 - 112266015

# TRAVEL & TOURISM'S CONTRIBUTION TO EMPLOYMENT

Travel & Tourism generated 4,332,457 jobs directly in 2022 (3.2% of total employment). This includes employment by hotels, travel agents, airlines and other passenger transportation services (excluding commuter services). It also includes, for example, the activities of the restaurant and leisure industries directly supported by tourists.

By 2033, Travel & Tourism will account for 6,163,000 jobs directly (4.1% of total employment), an increase of 3.3% pa from 2023.

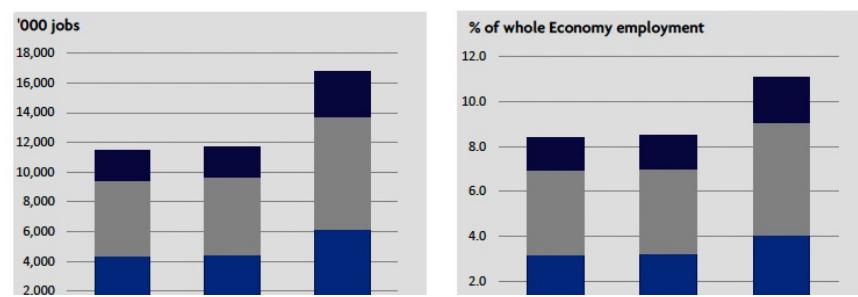
## Indonesia: Direct Contribution of Travel & Tourism to Employment



The total contribution of Travel & Tourism to employment (including wider effects from investment, the supply chain and induced income impacts, see page 3) was 11,437,300 jobs in 2022 (8.4% of total employment).

By 2033, Travel & Tourism is forecast to support 16,811,565 jobs (11.1% of total employment), an increase of 3.7% pa since 2023.

## Indonesia: Total Contribution of Travel & Tourism to Employment



## Introduction

Unemployment is a prevalent social issue in many countries, and the creation of job opportunities across various sectors can play a significant role in addressing this issue.

The World Travel & Tourism Council (WTTC) provides data showing the overall contribution of the travel and tourism (T&T) sector to employment, including broader effects from investment, the supply chain, and induced income impacts.

Literature reviews reveal that tourism has become a vital industry with a global impact, particularly in developing nations (Lu *et al.*, 2020; Mahadevan and Suardi, 2019). Moreover, tourism not only creates job opportunities but also enhances income (Lee & Chang, 2008).

Source: Travel & Tourism Economic Impact 2023. <https://researchhub.wttc.org/product/world-economic-impact-report>



## Introduction

The tourism sector significantly contributes to the economy. Between 2015 and 2019, foreign tourist visits grew 11.47 percent, reaching 16.1 million people in 2019, with a foreign exchange value of USD 18.45 billion (BPS, 2020).



Domestic tourists made 282 million trips with IDR 291 trillion in spending. The sector employs 14.96 million people, contributing 4.97% to the economy, prompting the government to prioritize tourism for national economic growth.

## **Research Gap**

Literature reviews reveal that tourism has become a vital industry with a global impact, particularly in developing nations (Lu et al., 2020; Mahadevan and Suardi, 2019). Moreover, tourism not only creates job opportunities but also enhances income (Lee & Chang, 2008). However, there is a notable research gap in understanding how these factors, along with tourism development, impact economic performance and unemployment at the provincial level in Indonesia. Furthermore, the spatial dynamics of tourism's economic impact: how tourism growth in one province influences neighboring regions, remain underexplored.

## **Purposes of the Study**

The purpose of this study is to analyze the impact of tourism development on regional economic performance and unemployment in Indonesia, focusing on the 34 provinces from 2018 to 2020. Specifically, this research aims to:

- Investigate the role of human development, tourism-related activities, and investment (both foreign and domestic) in influencing Gross Regional Domestic Product (GRDP) and unemployment rates at the provincial level.
- Examine the spatial spillover effects of tourism growth and its broader economic implications.
- Identify the localized factors that drive economic outcomes and unemployment, accounting for within-province variations.

## Literature Review – Economic Performance & Tourism Development

**HDI:** the role of human capital, measured through education, health, and living standards, in driving economic growth. Studies such as those by Barro (1996) and Becker (1994) support the notion that investments in human development lead to enhanced economic productivity and growth.

**Investment:** FDI and DDI can bring advanced technologies, management practices, and access to international markets, which are critical for economic growth (Borensztein, De Gregorio, & Lee, 1998; Alfaro, Chanda, Kalemli-Ozcan, & Sayek, 2004).

**Population Density:** The negative impact of population density on GRDP in earlier years suggests that high population concentrations can lead to congestion, strain on infrastructure, and resource depletion, which negatively affect economic productivity. This is consistent with urban economic theories that highlight the costs of overpopulation (Glaeser, 1999).

**Tourism:** International tourists contribute significantly to economic growth through higher spending, domestic tourism may not provide the same level of economic benefit, potentially due to lower spending or inadequate infrastructure to support domestic tourist activities (Blanchard & Katz, 1992).

## Literature Review – Economic Performance & Tourism Development

**Tourism:** International tourists contribute significantly to economic growth through higher spending, domestic tourism may not provide the same level of economic benefit, potentially due to lower spending or inadequate infrastructure to support domestic tourist activities (Blanchard & Katz, 1992).

**Spatial Dependencies:** Local factors, such as provincial policies, governance, and local economic conditions, play more critical roles in determining economic outcomes than regional spillovers (Blanchard & Katz, 1992).

## Literature Review – Unemployment & Regional Dynamics

**HDI:** While human development enhances economic productivity, it does not directly translate into job creation unless accompanied by appropriate labor market policies and job opportunities (Todaro & Smith, 2003).

**Tourism:** The tourism sector, despite its potential to generate employment, may not provide stable or sufficient job opportunities to affect overall unemployment rates significantly. The seasonal nature of tourism jobs and concentration of tourism benefits in specific areas might explain this finding (Sinclair & Stabler, 1997).

**Investment:** Investments may not be directed toward labor-intensive sectors or that the scale of investments is insufficient to create substantial employment. Aghion & Howitt (1998) suggest that for investments to effectively reduce unemployment, they need to target sectors with high employment potential and ensure that the benefits are widely distributed.

## Literature Review – Unemployment & Tourism Dynamics

**Population Density:** While higher population density can theoretically provide a larger labor pool and stimulate economic activity, it can also lead to higher competition for jobs and urban challenges that negate potential employment benefits (Lewis, 1954).

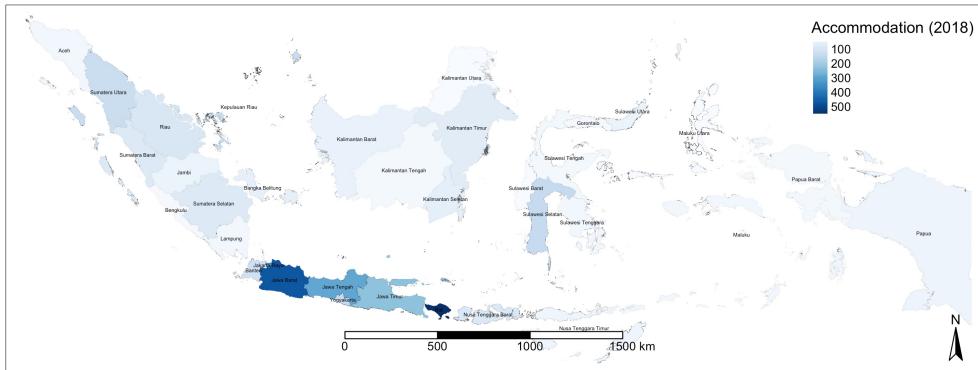
**Spatial Dependencies:** Provincial labor markets operate relatively independently, with localized economic conditions, policies, and governance quality playing more critical roles in shaping unemployment rates. Studies on regional labor markets emphasize the importance of local economic policies and labor market interventions in addressing unemployment (Blanchard & Katz, 1992).

## Hypotheses

- **H1:** Human Development Index (HDI) has a significant positive impact on Gross Regional Domestic Product (GRDP) in Indonesian provinces.
- **H2:** Tourism development, measured through logged accommodation and the number of foreign and domestic tourists, positively influences GRDP in Indonesian provinces.
- **H3:** Foreign Direct Investment (FDI) & Domestic Direct Investment positively influences GRDP in Indonesian provinces.
- **H4:** Population density negatively affects GRDP in Indonesian provinces.
- **H5:** There are significant spatial spillover effects of tourism development on GRDP, indicating that economic conditions in one province are influenced by tourism activities in neighboring provinces.
- **H6:** HDI, tourism development, FDI, DDI, and population density negatively affects unemployment rates in Indonesian provinces.
- **H7:** Unemployment rates in Indonesian provinces are not significantly influenced by spatial interactions with neighboring provinces.

## Research Questions

- **RQ1:** How does the Human Development Index (HDI) influence the Gross Regional Domestic Product (GRDP) across Indonesian provinces from 2018 to 2020?
- **RQ2:** What is the impact of tourism development, including accommodation and the number of foreign and domestic tourists, on the GRDP in Indonesian provinces?
- **RQ3:** How do Foreign Direct Investment (FDI) and Domestic Direct Investment (DDI) affect the GRDP in Indonesian provinces?
- **RQ4:** What is the effect of population density on GRDP in Indonesian provinces?
- **RQ5:** Are there significant spatial spillover effects of tourism development on the economic performance (GRDP) of neighboring provinces?
- **RQ6:** What are the impacts of HDI, tourism development, FDI, DDI, and population density on unemployment rates in Indonesian provinces?
- **RQ7:** To what extent do unemployment rates in Indonesian provinces exhibit spatial dependencies with neighboring provinces?

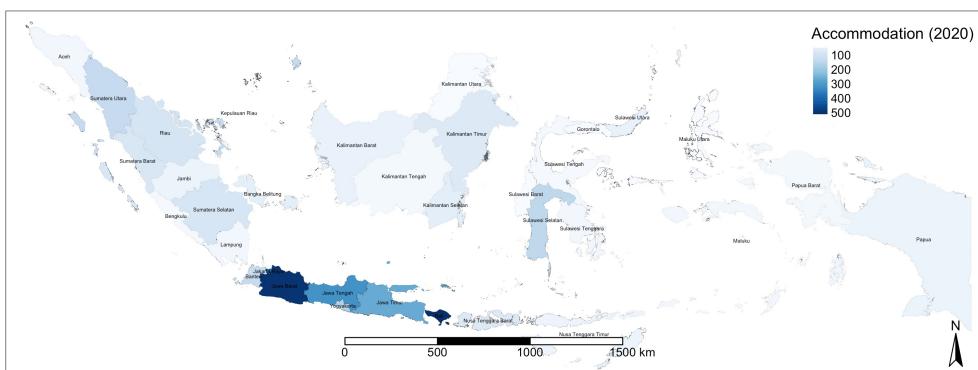
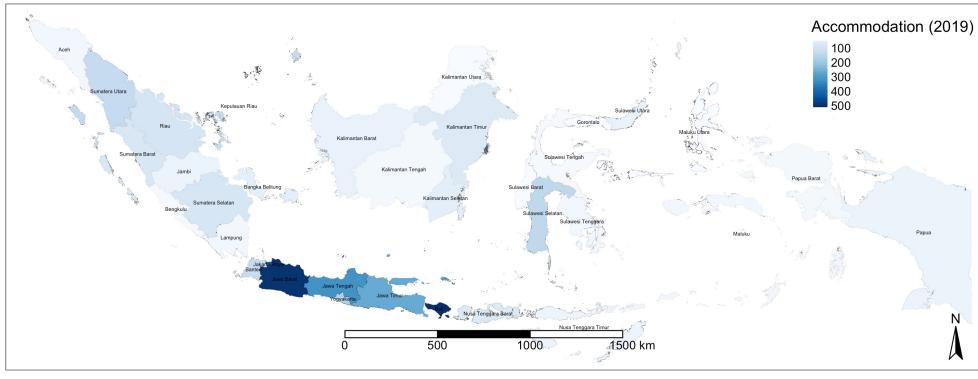


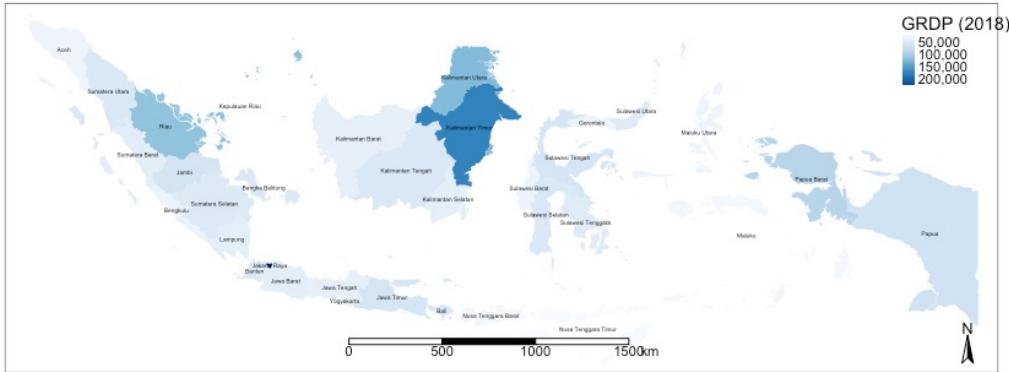
## Infrastructure Condition

A strong tourism infrastructure is indicated by the large number of accommodation options.

The epicenters of infrastructure are focused on two main islands for tourism: Bali and Java Island. This suggests a well-established tourism infrastructure and a high demand for accommodation services.

In contrast, other islands still have fewer accommodation options, such as North Maluku and North Kalimantan, indicating a less developed tourism infrastructure.

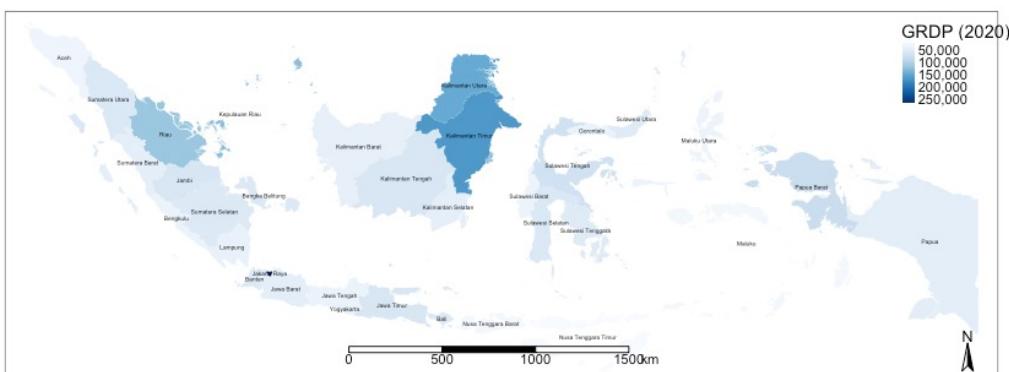
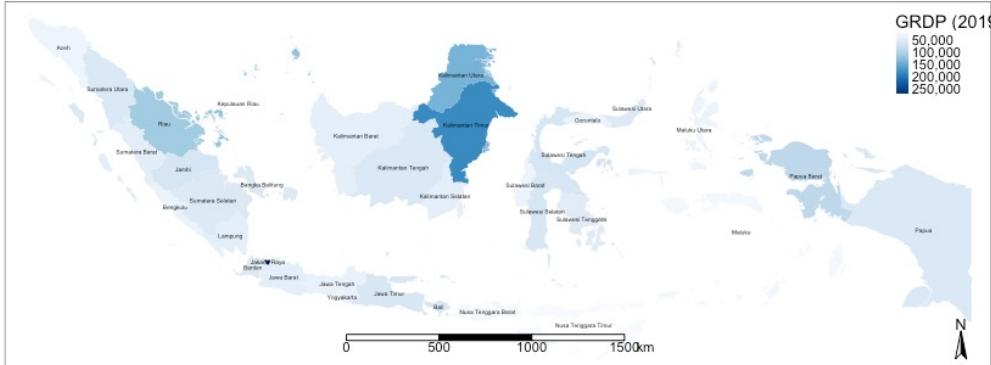


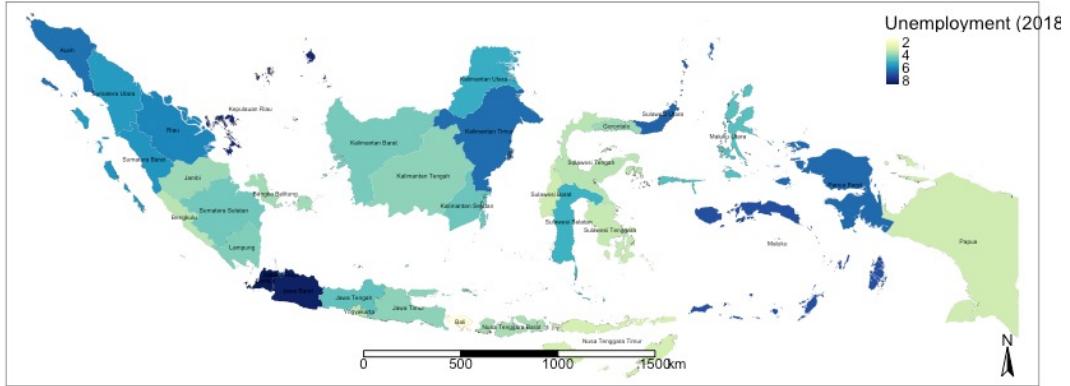


## GRDP

Jakarta had the highest GRDP, followed by Kalimantan Timur throughout three years.

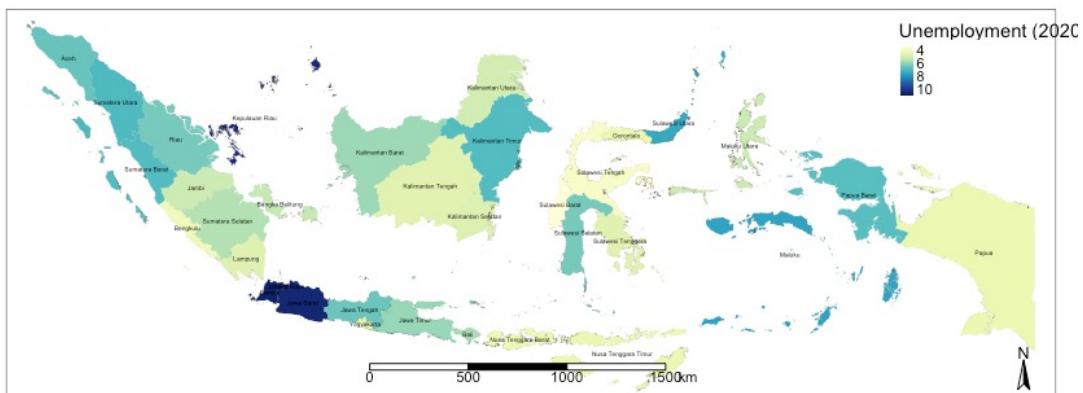
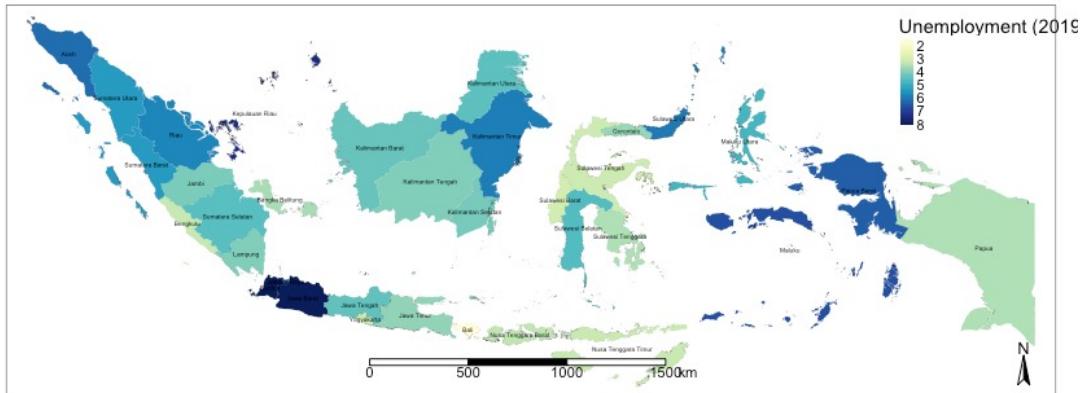
Jakarta's well-developed infrastructure makes it a key center for trade and business. Moreover, Kalimantan Island, especially Kalimantan Timur, has abundant coal, oil, and natural gas contribute significantly to East Kalimantan's GRDP.



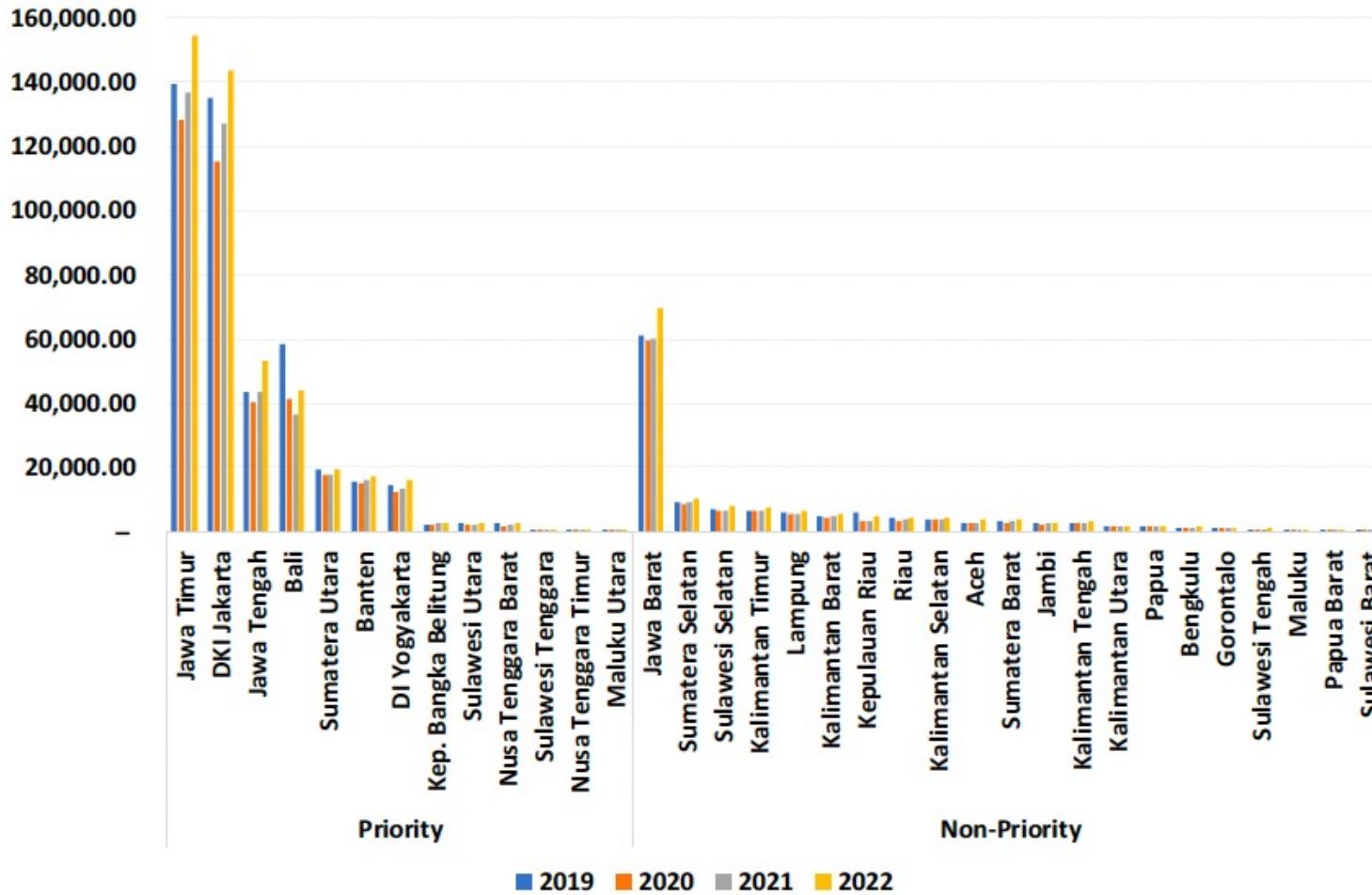


## Unemployment

Over the three years, the unemployment rates across Indonesian provinces demonstrate notable regional disparities and temporal fluctuations. The western provinces generally faced higher unemployment, with varying trends in the central and eastern regions.



*The regional distribution of  
Tourism Gross Regional Domestic Product (TGRDP)*



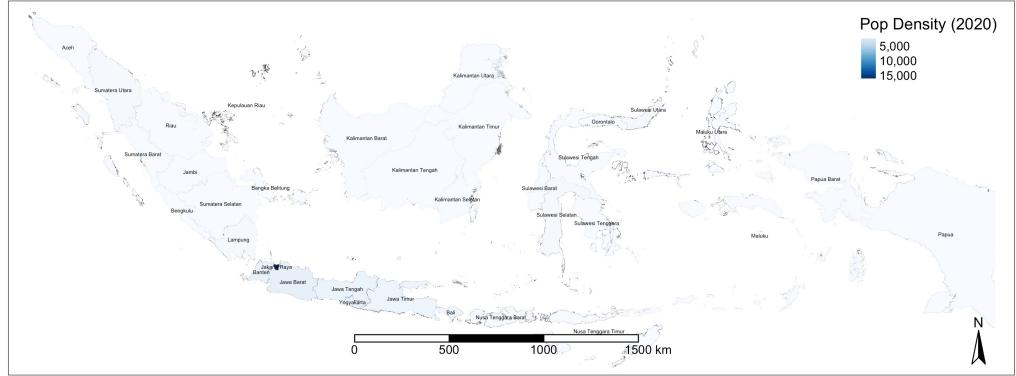
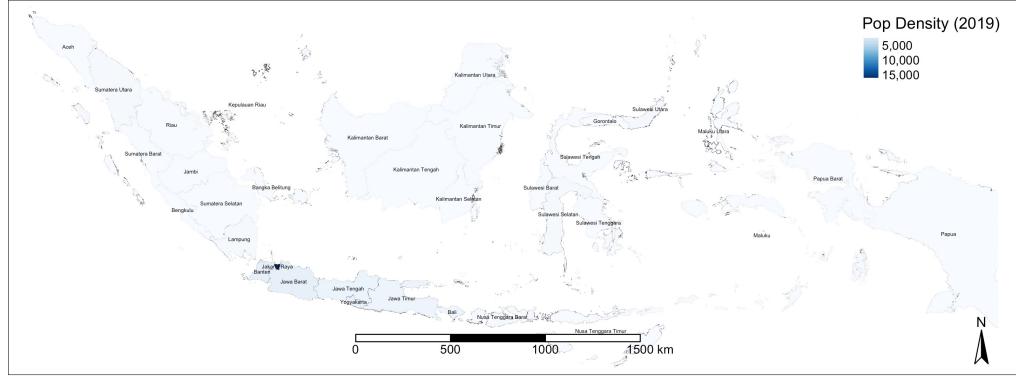
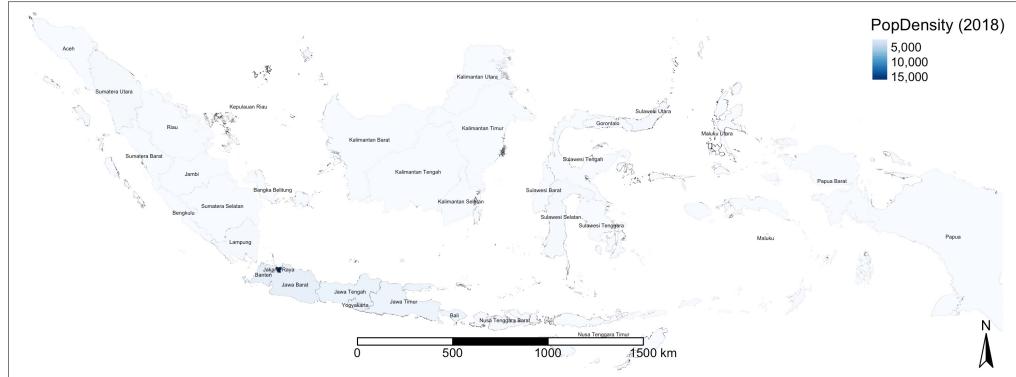
## **Tourism Gross Regional Domestic Product (TGRDP)**

TRGDP refers to the total economic output generated by the hotel and restaurant sectors within a specific region or province.

There is a significant contrast between the provinces on Java Island and those on other islands, except Bali, which serves as a tourism hub.

Java Island and Bali have good infrastructure making it well-connected to the rest of Indonesia and the world through international airports, making it easy for tourists to travel to Java from other parts of Indonesia and the world.

Source(s): BPS (2022) and BPS (2023)

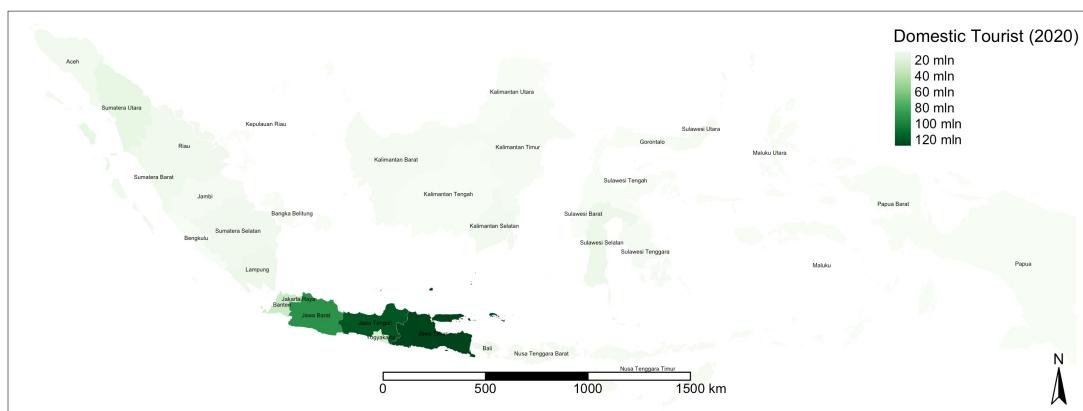
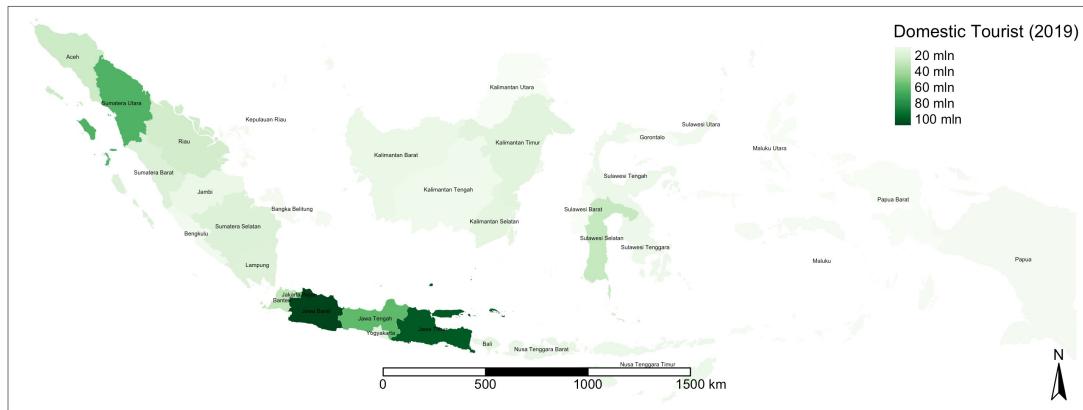
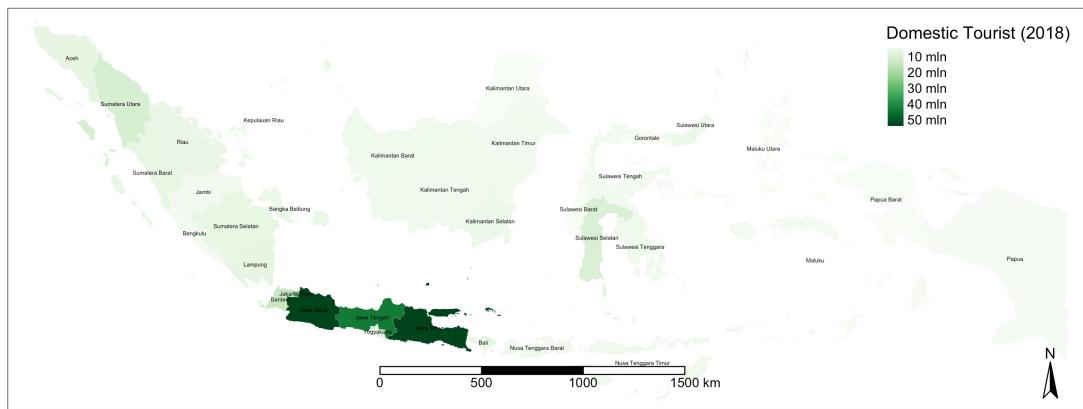


## Population Density

Higher population densities indicate more densely populated provinces.

The population distribution is concentrated on Java Island, particularly in major urban centers like Jakarta and Yogyakarta, as well as in other key tourist destinations such as Bali. These areas often serve as established hubs for commerce and tourism.

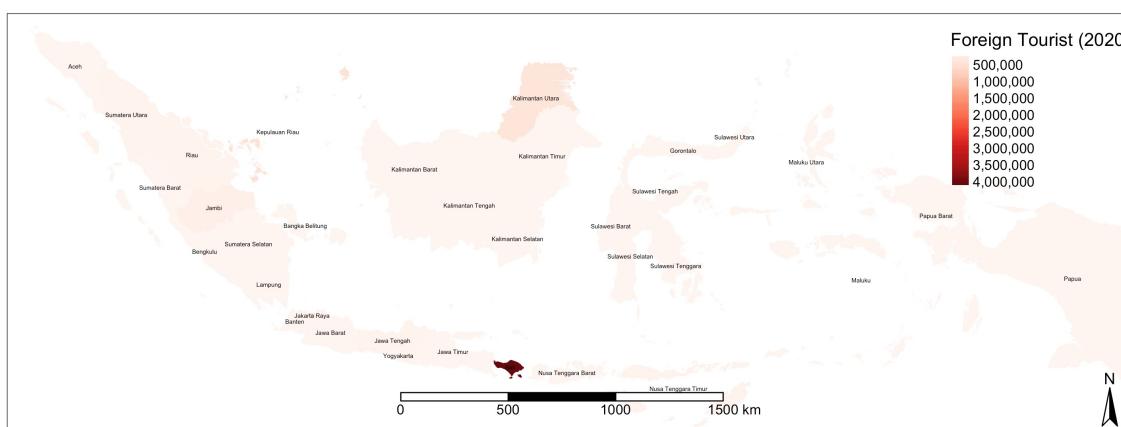
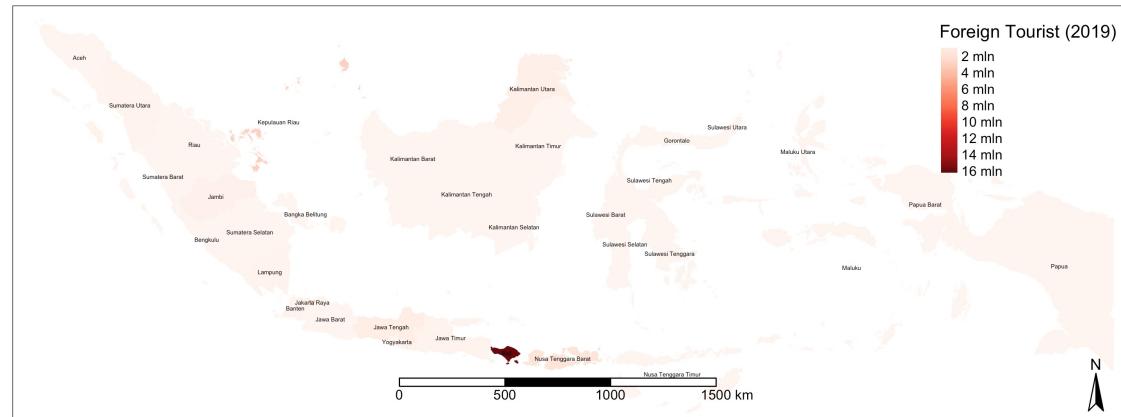
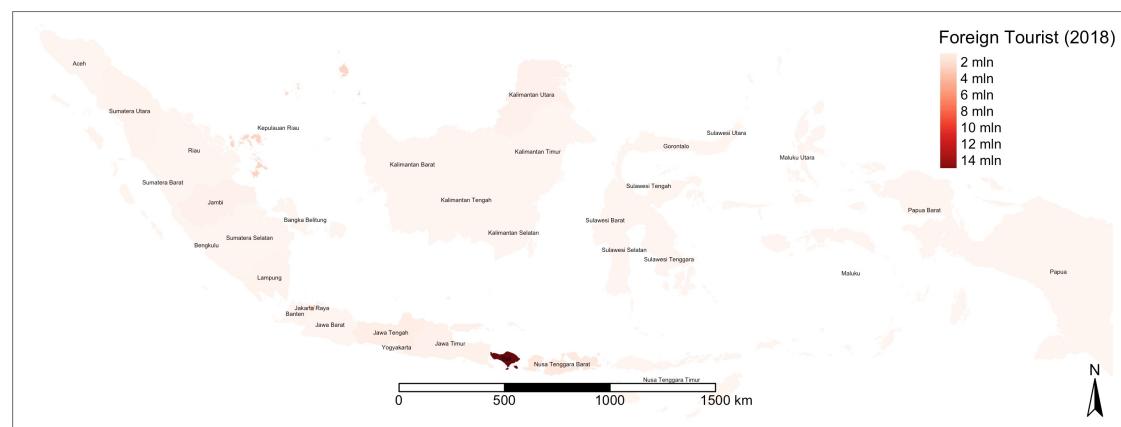
In contrast, provinces like Center Kalimantan and West Papua have lower population densities, suggesting more scattered populations and less urbanization.



## Number of Domestic Tourists

In each consecutive year, Java, particularly the western part where Jakarta is located, exhibits the darkest coloring. This consistent pattern suggests that areas like Jakarta and its surroundings remain the most visited destinations by domestic tourists.

These regions have a high concentration of domestic tourism due to their modern infrastructure, diverse attractions, and skilled workforce.



## Number of Foreign Tourists

Bali Island stands out as the primary destination for the majority of foreign tourists.

Bali's unique blend of cultural richness, natural beauty, and well-established hospitality services makes it a favored destination for international tourists. This preference directly fuels tourism employment, as the arrival of foreign visitors demands a larger workforce for various tourism-related services, from accommodations and dining to entertainment and transportation, driving substantial job creation on the island.

# Definition of Variables and Data Sources for Estimate Model

Data	Definition	Unit	Source
<b>Macroeconomy Condition</b>			
GDP regional	The economic output of a region. It indicates the economic productivity and standard of living of individuals within the region.	Thousand rupiahs	Statistic Indonesia
Unemployment rate	The percentage of the labor force that is unemployed and actively seeking employment. It is a key indicator of labor market health and economic stability within a region.	Percent	Statistic Indonesia
Foreign Direct Investment (FDI)	Overseas investments in local businesses.	Million US\$	Statistic Indonesia
Domestic Direct Investment (DDI)	Local investments in domestic enterprises.	Billion rupiahs	Statistic Indonesia
Number of tourism employment	The count of jobs within the tourism sector.	Person	Ministry of Tourism and Creative Economy
<b>Human Capital</b>			
Human Development Index	A measure combining life span, education, and income to assess a country's social and economic development.	Index	Statistic Indonesia
<b>Infrastructure Condition</b>			
Number of accommodations	The count of tourist lodgings.	Unit	Statistic Indonesia
<b>Tourism Condition</b>			
Number of foreign tourists	Visitors from abroad for travel or leisure.	Person	Statistic Indonesia
Number of domestic tourists	Local residents traveling within their own country for leisure or business.	Person	Statistic Indonesia
<b>Domestic Condition</b>			
Population density	The average number of people per unit area, reflecting how crowded a region is.	Person/sq.km	Statistic Indonesia

# Summary Statistics

Table: Summary Statistics for Estimation Sample

variable	observations	mean	sdl	min	max
IHDI	102	70.84	3.91	60.06	80.77
Iunemployment	102	5.18	1.85	1.40	10.95
IFDI	102	844.93	1202.63	6.50	5881.00
IDDI	102	11065.09	14009.43	50.90	62094.80
Iforeign_tourist	102	576234.86	2285795.47	138.00	16106954.00
Idomestic_tourist	102	15197392.29	25566051.28	211975.00	126676862.00
Itourism_employment	102	594632.10	924061.03	43206.00	4585478.00
IGRDP	102	61802.71	47487.94	18418.00	268052.00
Iaccommodation	102	102.69	133.39	1.00	551.00
Ipop_density	102	737.86	2670.94	9.00	15907.00
Ilog_HDI	102	4.26	0.06	4.10	4.39
Ilog_unemployment	102	1.58	0.36	0.34	2.39
Ilog_FDI	102	5.76	1.59	1.87	8.68
Ilog_DDI	102	8.54	1.39	3.93	11.04
Ilog_foreign_tourist	102	10.47	2.50	4.93	16.59
Ilog Domestic_tourist	102	15.54	1.45	12.26	18.66
Ilog_tourism_employment	102	12.58	1.12	10.67	15.34
Ilog_GRDP	102	10.85	0.55	9.82	12.50
Ilog_accommodation	102	3.86	1.33	0.00	6.31
Ilog_pop_density	102	4.88	1.59	2.20	9.67

Overall, the table highlights significant variability across provinces.

In terms of economic development, investment, tourism activity, and infrastructure, diverse HDI values (mean: 70.84) and GRDP (mean: 61,802.71 billion IDR) indicate substantial differences in well-being among provinces.

Some provinces are more developed and prosperous, leading to unequal economic conditions.

# Methodology

This study applies fixed-effects estimation and spatial data analysis to examine the impact of tourism-related factors on Gross Regional Domestic Product (GRDP) and unemployment rates across Indonesian provinces from 2018 to 2020.

## Fixed-effects model

### Model 1 (GRDP) - Before VIF

$$\ln(\text{grdp})_{it} = \beta_0 + \beta_1 \ln(\text{domestic\_tourist})_{it} + \beta_2 \ln(\text{foreign\_tourist})_{it} + \beta_3 \text{hdi}_{it} \\ + \beta_4 \ln(\text{accommodation})_{it} + \beta_5 \ln(\text{fdi})_{it} + \beta_6 \ln(\text{ddi})_{it} \\ + \beta_7 \ln(\text{tourism\_employment})_{it} + \beta_8 \ln(\text{pop\_density})_{it} + \varepsilon_{it}$$

### Model 1 (GRDP) - After VIF

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

### Model 2 (Unemployment)

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

## Methodology - Cont'd

### Spatial lag analysis

#### Model 1 (GRDP)

$$\begin{aligned} \ln(grdp) = & \beta_0 + \beta_1 \ln(domestic\_tourist) + \beta_2 \ln(foreign\_tourist) + \beta_3 hdi \\ & + \beta_4 \ln(accommodation) + \beta_5 \ln(fd़i) + \beta_6 \ln(ddi) + \beta_7 \ln(pop\_density) \\ & + \rho W \ln(grdp) + \varepsilon \end{aligned}$$

#### Model 2 (Unemployment)

$$\begin{aligned} \ln(unemployment) = & \beta_0 + \beta_1 \ln(domestic\_tourist) + \beta_2 \ln(foreign\_tourist) + \beta_3 hdi \\ & + \beta_4 \ln(accommodation) + \beta_5 \ln(fd़i) + \beta_6 \ln(ddi) + \beta_7 \ln(pop\_density) \\ & + \rho W \ln(grdp) + \varepsilon \end{aligned}$$

# Model 1 - GRDP

## Panel Data Regression

### Fixed Effect Model

```
Call:  
plm(formula = log_grdp ~ HDI + log_accommodation + log Domestic_tourist +  
    log_Foreign_tourist + log_FDI + log_DDI + log_tourism_employment +  
    log_pop_density, data = pdata, model = "within")  
  
Balanced Panel: n = 34, T = 3, N = 102  
  
Residuals:  
    Min. 1st Qu. Median 3rd Qu. Max.  
-0.0549139 -0.0114719 -0.0005785 0.0140602 0.0612207  
  
Coefficients:  
              Estimate Std. Error t-value Pr(>|t|)  
HDI          0.0837726 0.0126903 6.6013 1.193e-08 ***  
log_accommodation 0.0744347 0.0137451 5.4154 1.134e-06 ***  
log Domestic_tourist 0.0058087 0.0050952 1.1400 0.25880  
log_Foreign_tourist 0.0071825 0.0038337 1.8735 0.06587 .  
log_FDI          0.0117490 0.0056253 2.0886 0.04100 *  
log_DDI          -0.0109227 0.0056777 -1.9238 0.05913 .  
log_tourism_employment 0.0764622 0.0622825 1.2277 0.22437  
log_pop_density   -0.8447494 0.0997411 -8.4694 7.785e-12 ***  
---  
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1  
  
Total Sum of Squares: 0.20335  
Residual Sum of Squares: 0.041321  
R-Squared: 0.7968  
Adj. R-Squared: 0.65795  
F-statistic: 29.4101 on 8 and 60 DF, p-value: < 2.22e-16
```

### VIF Test for Model 1 - GRDP

```
> # Calculate VIF values  
> vif_values <- calculate_vif(model1)  
> print(vif_values)  
      HDI log_accommodation log Domestic_tourist log_Foreign_tourist  
3.103022        4.894634           4.374487         1.574933  
log_FDI          log_DDI log_tourism_employment log_pop_density  
2.157697        3.351033          12.912624         4.038913
```

## Panel Data Regression

# Model 1 – GRDP (After VIF)

### Fixed Effect Model

```
Call:  
plm(formula = log_grdp ~ HDI + log_accommodation + log Domestic_tourist +  
    log_foreign_tourist + 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|)  
HDI          0.0922581 0.0106870 8.6327 3.613e-12 ***  
log_accommodation 0.0757085 0.0137627 5.5010 7.909e-07 ***  
log Domestic_tourist 0.0050807 0.0050816 0.9998 0.32134  
log_foreign_tourist 0.0084713 0.0037025 2.2880 0.02562 *  
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
```

## Panel Data Regression

# Model 2 - Unemployment

### Fixed Effect Model

```
Call:  
plm(formula = log_unemployment ~ HDI + log_accommodation + log Domestic_tourist +  
    log_Foreign_tourist + 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|)  
HDI          0.107418  0.060013  1.7899  0.07843 .  
log_accommodation -0.012516  0.077285 -0.1619  0.87188  
log Domestic_tourist -0.032736  0.028536 -1.1472  0.25579  
log_Foreign_tourist -0.090018  0.020791 -4.3296 5.653e-05 ***  
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
```

### VIF Test for Model 2 - Unemployment

```
> # Calculate VIF values  
> vif_values <- calculate_vif(model2)  
> print(vif_values)  
      HDI log_accommodation log Domestic_tourist log_Foreign_tourist log_FDI  
2.009924        3.245420         2.946726        1.490878        1.647107  
log_DDI log_pop_density  
2.546177        3.052838
```

# Spatial Lag Analysis

## Model 1 - GRDP

Year: 2018

```
Call:lagsarlm(formula = log_grdp ~ HDI + log_accommodation + log Domestic_tourist +
log_foreign_tourist + log_FDI + log_DDI + 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
HDI	0.0729664	0.0218930	3.3329	0.0008596
log_accommodation	-0.0201964	0.1019536	-0.1981	0.8429713
log Domestic_tourist	-0.2292842	0.0903079	-2.5389	0.0111197
log_foreign_tourist	0.0166737	0.0344623	0.4838	0.6285111
log_FDI	0.0076066	0.0499975	0.1521	0.8790764
log_DDI	0.3107698	0.1028217	3.0224	0.0025077
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

Year: 2019

```
Call:lagsarlm(formula = log_grdp ~ HDI + log_accommodation + log Domestic_tourist +
log_foreign_tourist + log_FDI + log_DDI + 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
HDI	0.078871	0.025916	3.0434	0.002339
log_accommodation	0.083265	0.103582	0.8039	0.421478
log Domestic_tourist	-0.209647	0.136992	-1.5304	0.125927
log_foreign_tourist	0.047239	0.034646	1.3635	0.172738
log_FDI	0.127347	0.053697	2.3716	0.017711
log_DDI	0.127222	0.104011	1.2232	0.221270
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

# Spatial Lag Analysis

## Model 1 - GRDP

Year: 2020

```
Call:lagsarlm(formula = log_grdp ~ HDI + log_accommodation + log Domestic_tourist +
log_foreign_tourist + log_FDI + log_DDI + 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
HDI	0.0729664	0.0218930	3.3329	0.0008596
log_accommodation	-0.0201964	0.1019536	-0.1981	0.8429713
log Domestic_tourist	-0.2292842	0.0903079	-2.5389	0.0111197
log_foreign_tourist	0.0166737	0.0344623	0.4838	0.6285111
log_FDI	0.0076066	0.0499975	0.1521	0.8790764
log_DDI	0.3107698	0.1028217	3.0224	0.0025077
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

## Spatial Lag Analysis

# Model 2 - Unemployment

Year: 2018

```
Call:lagsarlm(formula = log_unemployment ~ HDI + log_accommodation + log Domestic_tourist + log_foreign_tourist + log_FDI + log_DDI + 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
HDI	0.02968263	0.01976032	1.5021	0.1331
log_accommodation	-0.06840725	0.08400009	-0.8143	0.4155
log Domestic_tourist	0.13280666	0.12290064	1.0806	0.2799
log_foreign_tourist	-0.01840987	0.03203438	-0.5747	0.5655
log_FDI	0.04597098	0.05004302	0.9186	0.3583
log_DDI	0.00018244	0.06284947	0.0029	0.9977
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

Year: 2019

```
Call:lagsarlm(formula = log_unemployment ~ HDI + log_accommodation + log Domestic_tourist + log_foreign_tourist + log_FDI + log_DDI + 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
HDI	0.029763	0.021151	1.4072	0.15937
log_accommodation	-0.004075	0.083899	-0.0486	0.96126
log Domestic_tourist	0.100752	0.113261	0.8896	0.37371
log_foreign_tourist	-0.016045	0.028556	-0.5619	0.57421
log_FDI	0.074245	0.044412	1.6717	0.09458
log_DDI	-0.065349	0.085366	-0.7655	0.44396
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

## Spatial Lag Analysis

## Model 2 - Unemployment

Year: 2020

```
Call:lagsarlm(formula = log_unemployment ~ HDI + log_accommodation + log Domestic_tourist + log_Foreign_tourist + log_FDI + log_DDI + log_pop_density, data = pdata_cross_2020, listw = lw)

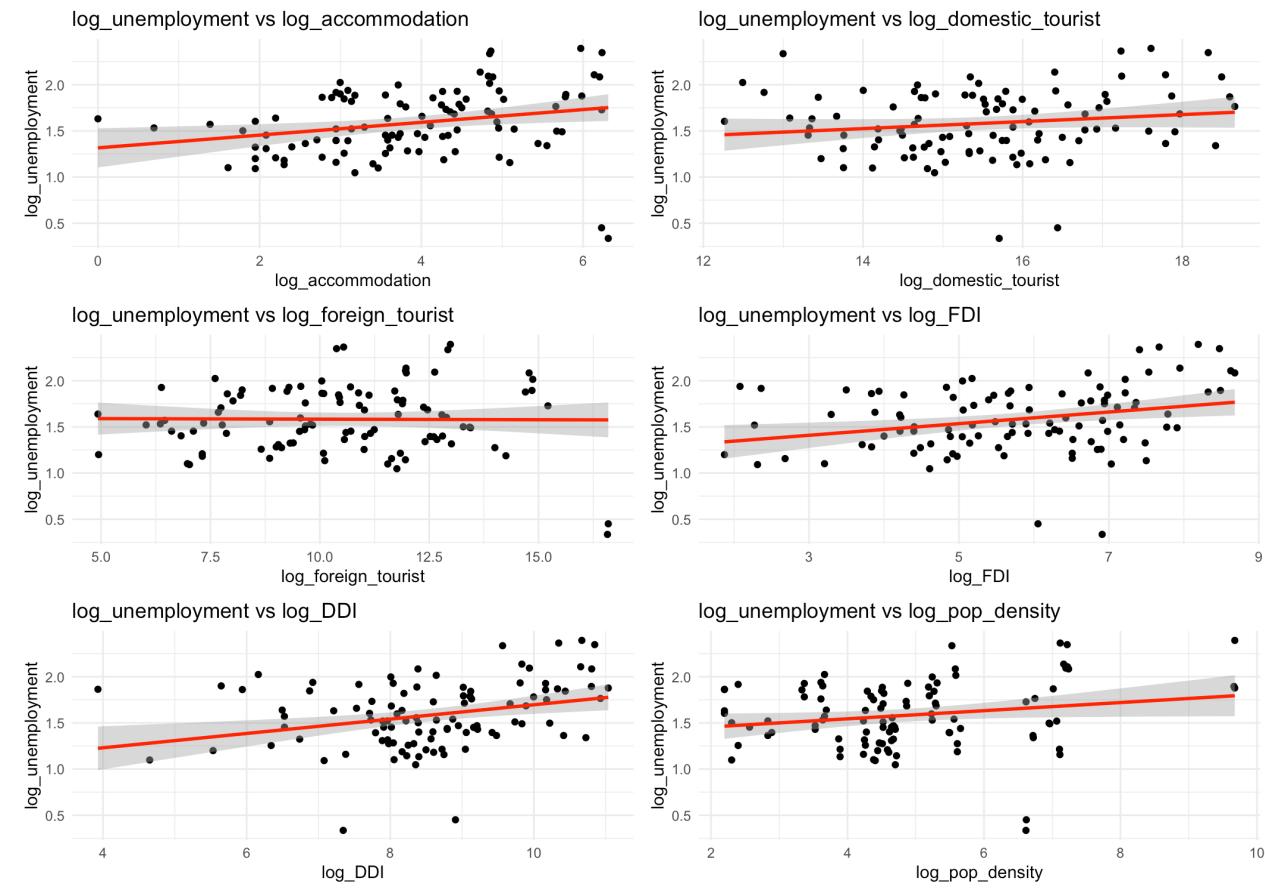
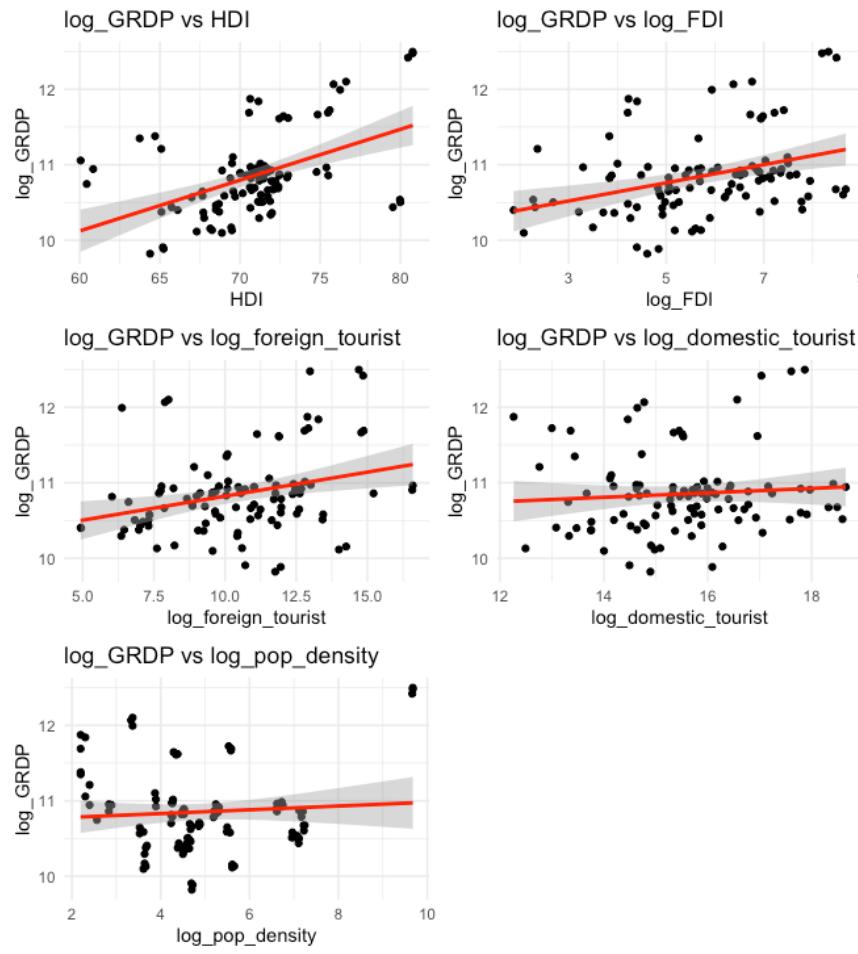
Residuals:
    Min      1Q   Median      3Q      Max 
-0.372512 -0.135530 -0.022663  0.065548  0.427454 

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

## Panel Data Regression – Cont'd

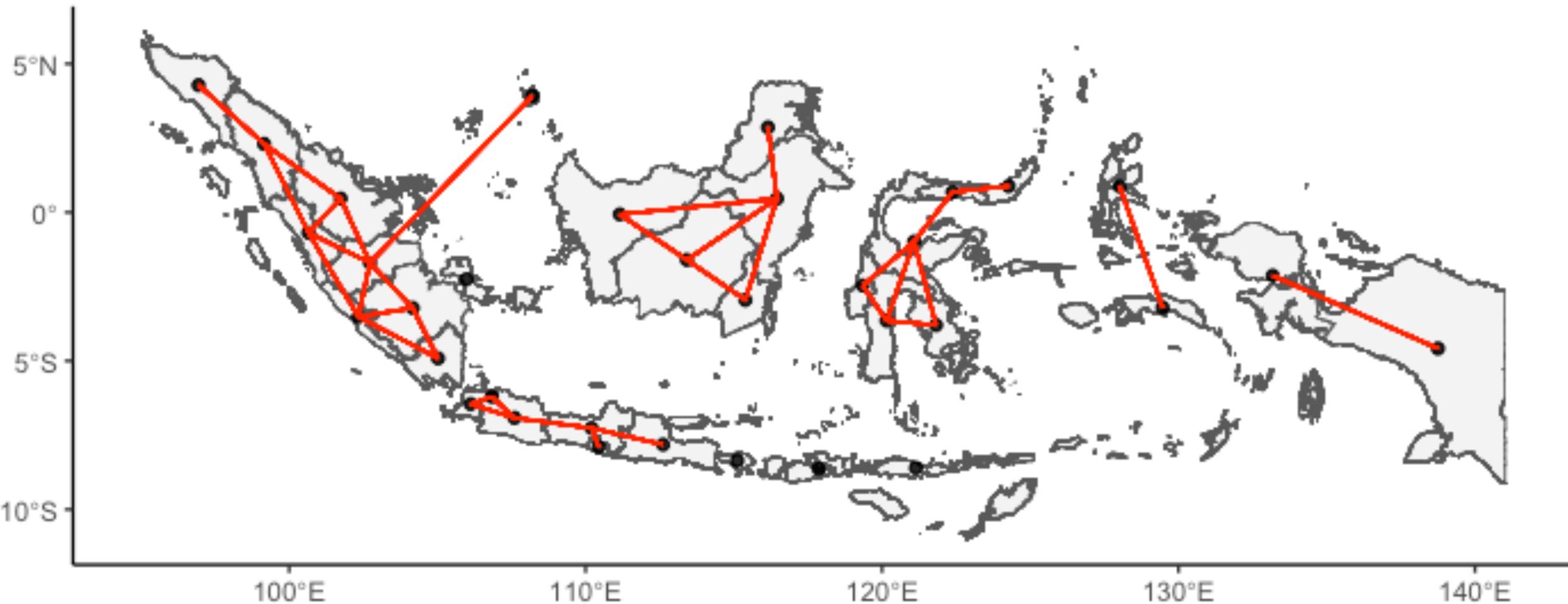


**Model 1 - GRDP**

**Model 2 - Unemployment**

# Contiguity-based Neighbors Map

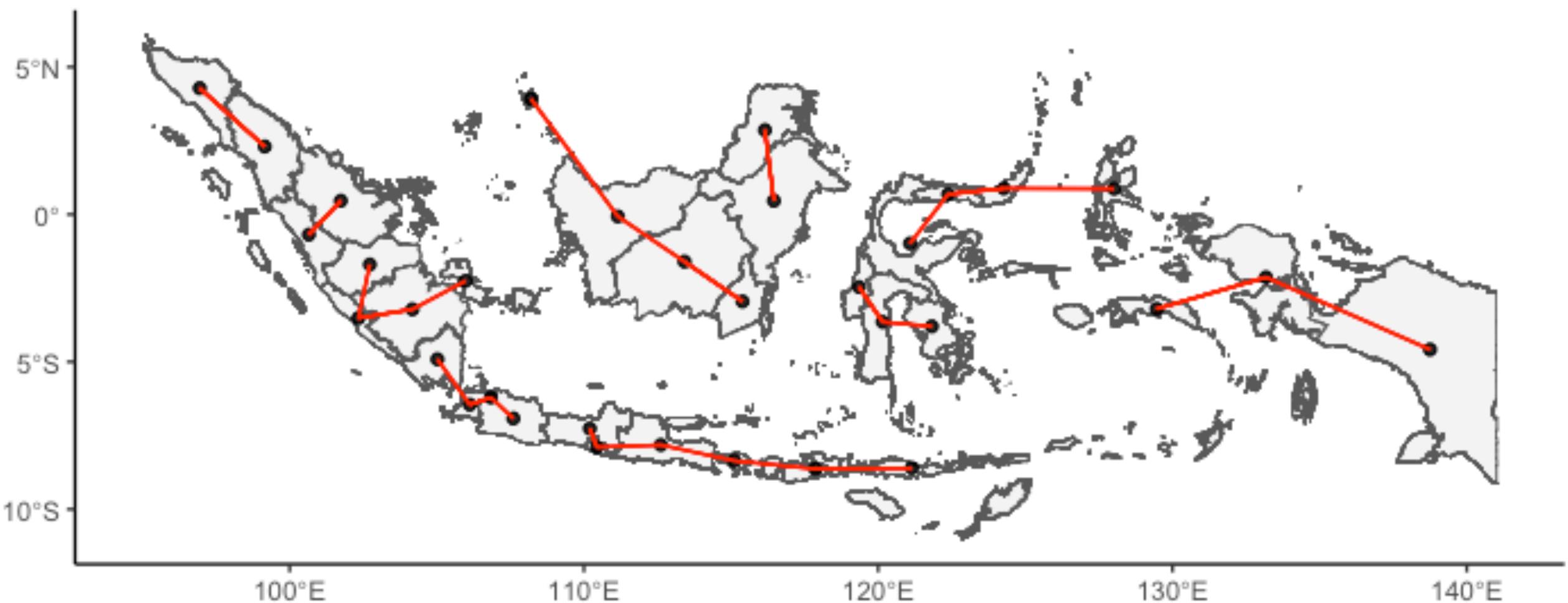
## Using Queen's Case Neighbor Definition



```
#Contiguity-based neighbors
neighbors <- poly2nb(FinalData, queen = TRUE)
summary(neighbors)
neighbors[[1]]
idn.centroid <- st_centroid(st_geometry(FinalData),
                             of_largest_polygon = TRUE)
idn.queenlines <- nb2lines(nb = neighbors,
                           coords = idn.centroid,
                           as_sf = TRUE)
```

# Proximity-based Neighbors Map

Using count k-nearest centroids Case Neighbor Definition



```
idn.knn <- knn2nb(knearneigh(idn.centroid, k = 3))
idn.dist <- dnearneigh(idn.centroid, d1=0, d2=5000)
idn.knlines <- nb2lines(nb = idn.knn, coords = idn.centroid, as_sf = TRUE)
idn.distlines <- nb2lines(nb = idn.dist, coords = idn.centroid, as_sf = TRUE)
```

```

> weights <- nb2listw(idn.knn, style = "W")
> weights$weights[[1]]
[1] 0.3333333 0.3333333 0.3333333
> FinalData$lag_GRDP <- lag.listw(weights , FinalData$log_GRDP)
>
> ggplot(FinalData, aes(x = log_GRDP, y = lag_GRDP)) +
+   geom_point(alpha = 0.3) +
+   geom_smooth(method="lm", color = "red") +
+   theme_minimal() +
+   labs(title = "GRDP by Provinces, Indonesia",
+       x = "GRDP",
+       y = "Spatial lag, GRDP",
+       caption = "Data source: 2018-2020 GRDP from Statistics Indonesia.
+       Spatial relationships based on K-nearest neighbors for each point."
+     )
`geom_smooth()` using formula = 'y ~ x'
> moran.test(FinalData$lag_GRDP, weights)

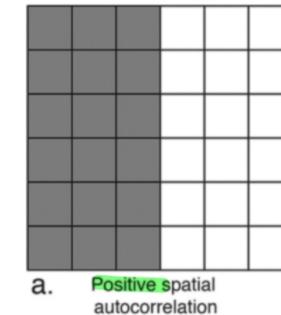
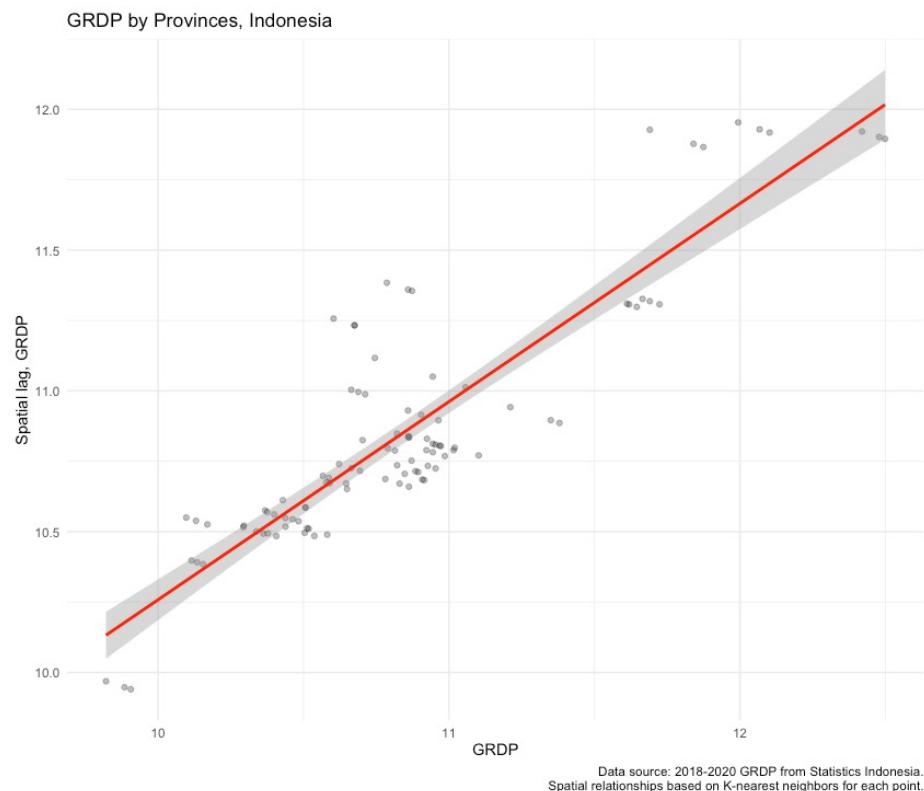
  Moran I test under randomisation

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

```

Note: The small p-value suggests that we reject the null hypothesis of spatial randomness in our dataset.



Each neighbor is assigned the weight 0.333. The scatterplot suggests a positive correlation between GRDP and its spatial lag.

The Moran's I statistic of 0.9193 is positive, which suggests that the sample is spatially clustered; i.e., positive spatial autocorrelation.

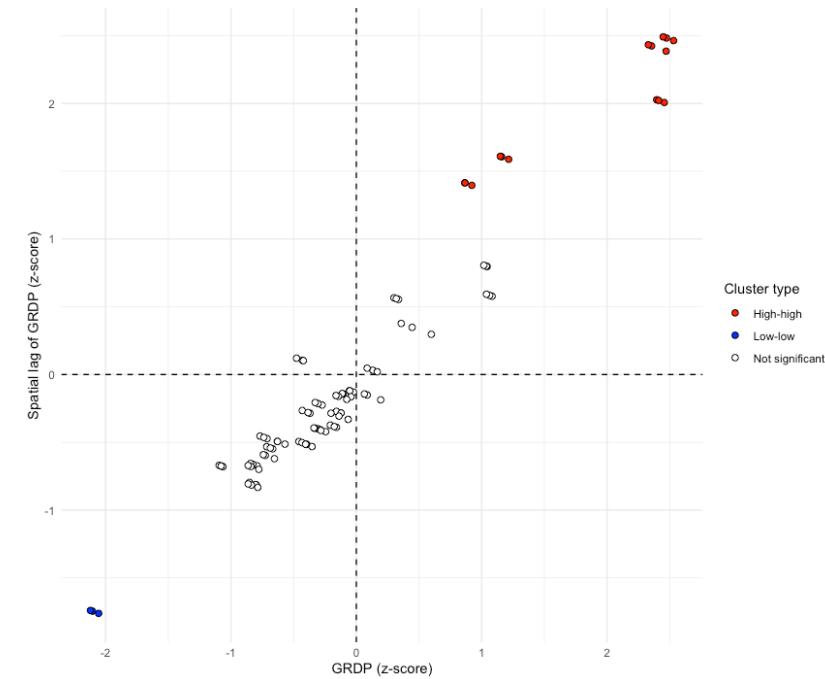
It means that provinces with higher GRDP tend to be located near one another, and provinces with lower GRDP also tend to be found in the same areas.

## Model 1 - GRDP

LISA Cluster Map for GRDP



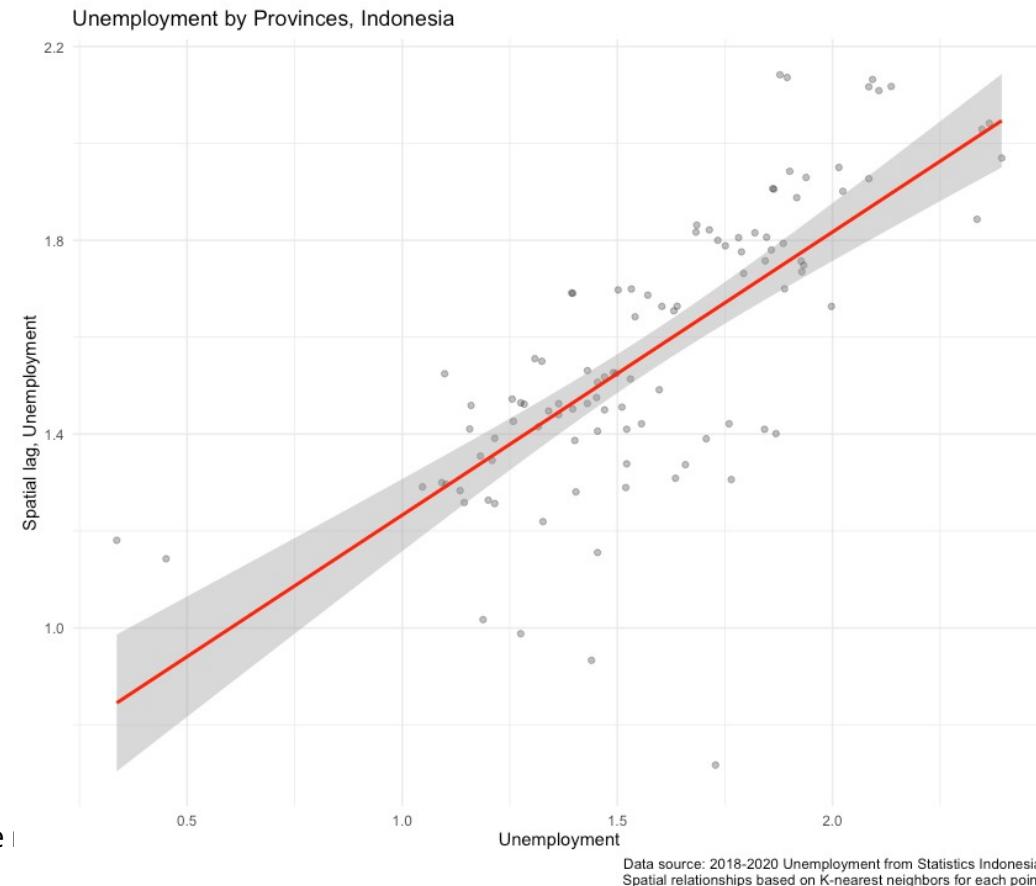
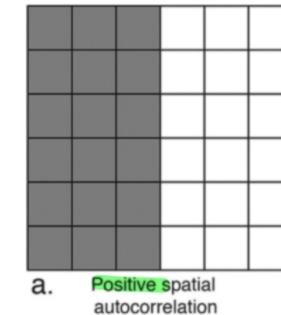
LISA Quadrant Plot



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

## Model 1 - GRDP



Each neighbor is assigned the weight 0.333. The scatterplot suggests a positive correlation between Unemployment and its spatial lag.

The Moran's I statistic of 0.8665 is positive, which suggests that the sample is spatially clustered; i.e., positive spatial autocorrelation.

It means that provinces with higher Unemployment tend to be located near one another, and provinces with lower unemployment also tend to be found in the same areas.

```
> 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
```

Note: The small p-value suggests that we reject the hypothesis of spatial randomness in our dataset.

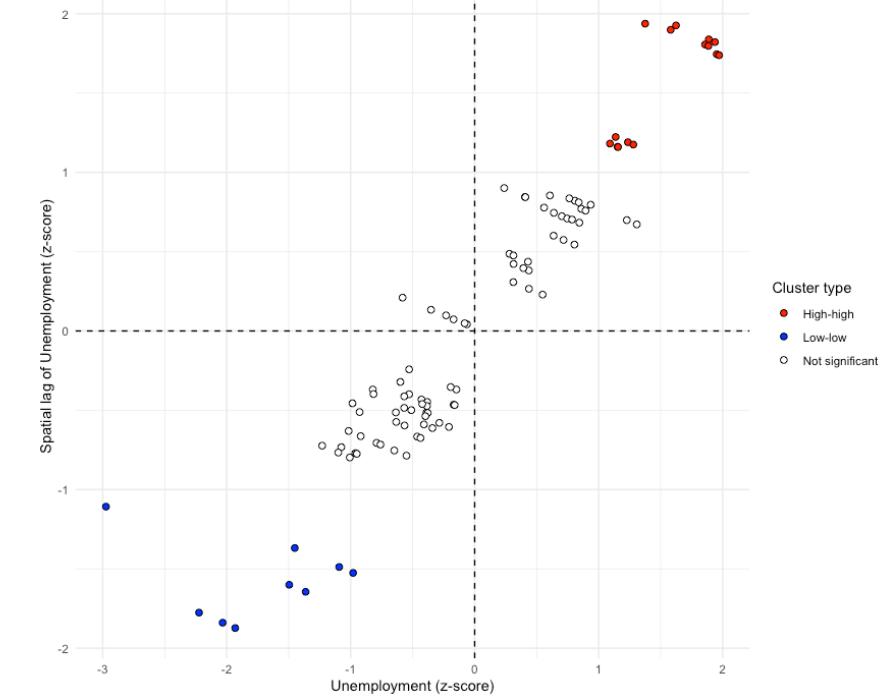
## Model 2 - Unemployment

LISA Cluster Map for Unemployment



Cluster type  
High-high  
Low-low  
Not significant

LISA Quadrant Plot for Unemployment



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 are also surrounded by provinces with lower Unemployment

## Model 2 - Unemployment

## Policy Implications

Balance Tourism Development

Enhance Human Development Initiatives

Attract and Manage FDI

Address Challenges Related to Population Density

## Policy Implications

Localized Economic Policies

Targeted Job Creation Programs

Promote Labor-Intensive Investments

Address Structural Unemployment



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The background of the slide is a collage of various Indonesian landscapes and landmarks. It includes a large green rock formation on the left, a volcano with red lava flows in the center, a Komodo dragon in the upper right, a traditional Balinese temple (Pura) reflected in water in the middle, and a dark blue diagonal shape on the right.

# Thank You!

Find us on:

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[112266015@g.nccu.edu.tw](mailto:112266015@g.nccu.edu.tw)